Providing Public Transport by Self-Driving Vehicles
User Preferences, Fleet Operation, and Parking Management

Winter, Konstanze

DOI
10.4233/uuid:9f5b51e1-4877-4e60-a9d0-69fa37fa834f

Publication date
2020

Document Version
Final published version

Citation (APA)
Winter, K. (2020). *Providing Public Transport by Self-Driving Vehicles: User Preferences, Fleet Operation, and Parking Management*. [Dissertation (TU Delft), Delft University of Technology]. TRAIL Research School. https://doi.org/10.4233/uuid:9f5b51e1-4877-4e60-a9d0-69fa37fa834f

Providing Public Transport by Self-Driving Vehicles
User Preferences, Fleet Operation, and Parking Management

Konstanze Winter

Delft University of Technology, 2020

Cover illustration by Klaus Winter.
This research has been funded by the NWO TRAIL Graduate Program, grant-number: 022.005.030

Providing Public Transport by Self-Driving Vehicles
User Preferences, Fleet Operation, and Parking Management

Proefschrift

ter verkrijging van de graad van doctor
aan de Technische Universiteit Delft,
op gezag van de Rector Magnificus Prof. dr.ir. T.H.J.J. van der Hagen,
voorzitter van het College voor Promoties,
in het openbaar te verdedigen op donderdag 2 april 2020 om 15:00 uur

door

Margarethe Konstanze Elisabeth WINTER
Master of Science in Civil Engineering, Transport & Planning,
Delft University of Technology
geboren te München, Duitsland

Dit proefschrift is goedgekeurd door de promotoren.

Samenstelling promotiecommissie bestaat uit:

Rector Magnificus	voorzitter
Prof. dr. ir. B. van Arem	Technische Universiteit Delft, promotor
Dr. O. Cats	Technische Universiteit Delft, promotor
Dr. K. Martens	Technion – Israel Institute of Technology, promotor

Onafhankelijke leden:

Prof. dr. E. van Bueren	Technische Universiteit Delft
Prof. Dr. K. Nagel	Technische Universität Berlin, Duitsland
Prof. dr. S. Rasouli	Eindhoven University of Technology
Dr. F. Ciari	Polytechnique Montréal, Canada
Prof. dr. B. van Wee	Technische Universiteit Delft, reservelid

TRAIL Thesis Series no. T2020/07, the Netherlands Research School TRAIL

TRAIL
P.O. Box 5017
2600 GA Delft
The Netherlands
E-mail: info@rsTrail.nl

ISBN: 978-90-5584-262-9

Printed in the Netherlands.

Acknowledgement

This dissertation is the outcome of a research project that I conducted at the TU Delft in the past four years. The research project has been funded by the NWO Trail Graduate Programme, and I am grateful for having been given the opportunity to devise and conduct a research project according to my personal research interests.

The past four years have been a time of learning, reflection and growth for me. I want to thank everybody who made this possible. Foremost, I want to thank my supervisors, Oded Cats, Karel Martens, and Bart van Arem. Their kind and generous guidance, advice and support have been crucial in this process.

I also want to thank those who supported me on the way: Bahamonde Birke, María Alonso González, and Sander van Cranenburgh for offering their kind advice on the set-up of choice experiments and latent class models; Joschka Bischoff, Michal Maciejewski and Kai Nagel for their warm welcome in Berlin and for setting me on the right path for using MATSim; Conchita van der Stelt for her kind support in the final phase of finishing this dissertation. Veronica Alfano for being a motivating and inspiring teacher; Bert van Wee for creating opportunities for us Ph.D. candidates to look beyond our own noses; Joost Wien for his commitment and trusting me with his supervision; and my esteemed office-mates for their advice, friendship and support.

My gratitude also goes out to the research community for their valuable feedback, in particular to the independent members of my doctoral committee and the anonymous reviewers of the papers and conference contributions forming this thesis.

I wish to acknowledge the help provided by the technical and administrative staff of the Department of Transport and Planning and TRAIL Research School for their support and for letting me practice writing e-mails in Dutch with them,… ook als dat in het begin nog niet zo soepel liep.

I'd like to give my special thanks to my friends and family, who cheered me on all the way.

Content

List of Figures

List of Tables

Chapter 1 - Introduction

Self-driving vehicles possess distinctive characteristics that could change the way we use road infrastructure and the way we travel, and they present themselves with a unique set of opportunities and challenges. Which role self-driving vehicles could play one day depends on multiple stakeholders, among which: potential users, policymakers and, in case self-driving vehicles are not privately owned, the operator of transport services deploying self-driving vehicles in this thesis. It is analysed how the rules these stakeholders might set will shape the use and impacts of such vehicles. In particular, the focus is put on shared automated vehicles used to provide on-demand transport services.

The remainder of this chapter is organized as follows: In section 1.1, the concept of Shared Automated Vehicles is presented, followed by a discussion of current planning principles for centrally dispatched on-demand transport services (section 1.2). In section 1.3, the research objectives and research scope are outlined, followed by a section describing the research approach in brief (section 1.4). The main scientific and societal contributions are sketched in section 1.5. An outline of the dissertation and a short description of each chapter are presented in section 1.6.

1.1 Shared Automated Vehicles

Currently, privately owned cars are in use during less than 10% of their lifespan; the rest of the time they remain idly parked (Shoup, 2018). This creates serious issues in places where competition for space is fierce and land prices are high, such as cities and urban agglomerations (Mingardo, van Wee, & Rye, 2015). Car sharing is often seen as a solution to these problems, as the sequential sharing of vehicles would increase the vehicles' efficiency of use and might encourage users to not privately own a car (Nijland & van Meerkerk, 2017; Schmöller, Weikl, Müller, & Bogenberger, 2015). An elaborate overview of the different forms of sharing vehicles, and their underlying business models, can be found in Stocker and Shaheen (2016). The term "car-sharing" is today commonly used for forms of transport in which vehicles are shared sequentially, but is sometimes also applied to forms of transport in which vehicles are shared simultaneously, such as car-pooling or ride-hailing services (Drut, 2018; Winter, Cats, Martens, & van Arem, 2017). In the remainder of this thesis, the concept of "shared vehicles" is used for transport services in which vehicles are shared sequentially, and not simultaneously.

The acceptance of car-sharing gained momentum after developments in communication technologies enabled easy access to car-sharing systems via the smartphone (Mounce & Nelson, 2019), which can be seen from the exponential growth of car-sharing users in the last years. In Germany, for example, has the number of car-sharing users increased from 137,000 in the year 2009 to 2,460,000 in the year 2019 (statista, 2019). In the same time span grew the number of car-sharing vehicles from 1,832 to 51,149 in the Netherlands (KpVV CROW, 2019). Factors that influence the acceptance of car-sharing services are the size of the operational area, the price of the service, the fleet size and the resulting availability of vehicles, and the relative ease of parking car-sharing vehicles (Dowling & Kent, 2015; Kang, Hwang, & Park, 2016; Millard-Ball, Murray, Ter Schure, Fox, & Burkhardt, 2005; Paundra, Rook, van Dalen, & Ketter, 2017). Despite their increasing popularity are car-sharing services still small in the field of urban transport (Greenwald & Kornhauser, 2019), e.g. in the Netherlands, the current number of car-sharing vehicles is only 0.6% of the total fleet of all passenger cars in the country, which comprises 8,5 million vehicles (Centraal Bureau voor de Statistiek (CBS), 2019). This might change, however, once the technology for vehicle automation has progressed enough to offer car-sharing services with self-driving vehicles. The path towards this development is sketched in the following.

The technology for automating vehicles has matured enough to conduct trials and pilot studies with driverless vehicles around the world (Sperling, van der Meer, & Pike, 2018). Self-driving vehicles, also referred to as fully automated or autonomous vehicles, are expected to bring many benefits: they promise to be safer, improve network flow, unburden all passengers from the task of driving, grant more mobility-independence to people without driving licences and can be operated much cheaper than chauffeur-bound vehicles (Brown & Taylor, 2018; Greenwald & Kornhauser, 2019; Harper, Hendrickson, & Samaras, 2018; Regional Plan Association (RPA), 2017; Sperling et al., 2018). Self-driving vehicles possess the highest degree of automation (level 4 and 5 in the SAE classification[1]) and therefore do not require any intervention from a human driver. Level 4–vehicles are capable of performing all driving tasks in most, but not all conditions (e.g only on selected roads, with low driving speeds, or in favourable weather conditions), while level 5-vehicles can perform all driving tasks in all conditions (SAE International, 2018). In both cases is an intervention by a human driver in in theory possible, which is however not the case of the transport service envisioned in this thesis. Passengers of this transport service are not required to intervene at any point, which makes the provided transport service universally accessible. These levels of vehicle automation are achieved by equipping a vehicle with a combination of on-board sensors (e.g. radar, GPS, LIDAR, odometry) mapping the surroundings of the vehicle, advanced control systems processing the sensory information and vehicle communication systems that can transmit and receive information to and from other vehicles (V2V), infrastructural entities (V2I), or generally any entity that can participate in this exchange of information (V2X). This intensive communication between moving objects (the vehicle) with other moving objects and their static environment requires a highly connected environment aligned with the technical needs of level 4- or 5-vehicles. A vision of how the physical road environment for such vehicles could look like is

[1] SAE International is an U.S. based professional association developing industry standards. The SAE classification of standardized levels of driving automation, last updated in the year 2018, are currently a leading standard used to describe the different levels of automated vehicles.

described in (Farah, Erkens, Alkim, & van Arem, 2018). Whether self-driving vehicles will be a common sight in the near future depends on many factors, including further technological improvements, political considerations, legal agreements, the costs of the technology and the infrastructure they require, the success of the current pilots as well as the acceptance of such vehicles by the broader public (Greenwald & Kornhauser, 2019; Regional Plan Association (RPA), 2017; Sperling et al., 2018).

One possible way in which self-driving cars might be introduced first is as shared automated vehicles (SAV), also referred to as automated taxi or aTaxi (Greenwald & Kornhauser, 2019) or robotaxi (Nunes & Hernandes, 2019). SAV are commonly described as driverless vehicles operated as an on-demand public transport service. The travel experience for the users of such services will be similar to the one associated today with a trip in a taxi or a ride-hailing vehicle, with the exception that no human driver is involved – the service provided by SAV can thus be regarded as a sort of cross-over between car-sharing and ride-hailing services (Stocker & Shaheen, 2017).

SAV are believed to overcome obstacles linked to both, traditional car-sharing and to automated vehicles (Brown & Taylor, 2018; Fagnant & Kockelman, 2015; Stocker & Shaheen, 2017). The operation of conventional vehicles in a shared manner has several shortcomings that become obsolete if operating the same service with automated vehicles, and in return problems currently associated with the introduction of automated vehicles can be overcome by using them in a shared manner. How vehicle sharing and vehicle automation can profit from each other is described in the following. A visualisation of the key points illustrating the synergies between the concept of vehicle sharing and the technology of vehicle automation is shown in Figure 1.1.

One of the main issues regarding the efficiency of car-sharing services operated with non-self-driving vehicles is, that the vehicles have to be located within walking distance of their potential users (Krueger, Rashidi, & Rose, 2016b). Relocating idle vehicles is thus essential to the operation of car-sharing services, and can either be tackled by giving financial incentives to the customers to park the vehicles close to expected future demand hot-spots or by employing drivers that move the vehicles accordingly (Angelopoulos, Gavalas, Konstantopoulos, Kypriadis, & Pantziou, 2018; Ferrero, Perboli, Rosano, & Vesco, 2018; Weikl & Bogenberger, 2013). Both options are costly and not necessarily efficient approaches, which can be overcome if vehicles could simply drive themselves to the desired parking location. Another advantage of employing self-driving vehicles is, that everybody could make use of car-sharing services, and not just people who legally can, and actually want to, steer a car. These aspect has been shown to be an important reason for using ride-hailing services (Young & Farber, 2019). However, ride-hailing transport services bring their own set of problems, which can again partly be solved by employing automated vehicles. This would solve issues such as undesired driver conduct and non-cooperative behaviour between the vehicles due to the need of drivers to maximise their individual turnover instead of contributing to a system optimum (Cetin & Deakin, 2019).

For the above-mentioned reasons of operational and cost efficiency as well as issues linked to individual driver needs and driver conduct, major players in the business of ride-hailing services are reportedly currently pushing the development of self-driving vehicles (Conger, 2019; Ruehl, 2019; Somerville, 2018), in the hope that soon it could be possible to operate their fleets with self-driving vehicles.

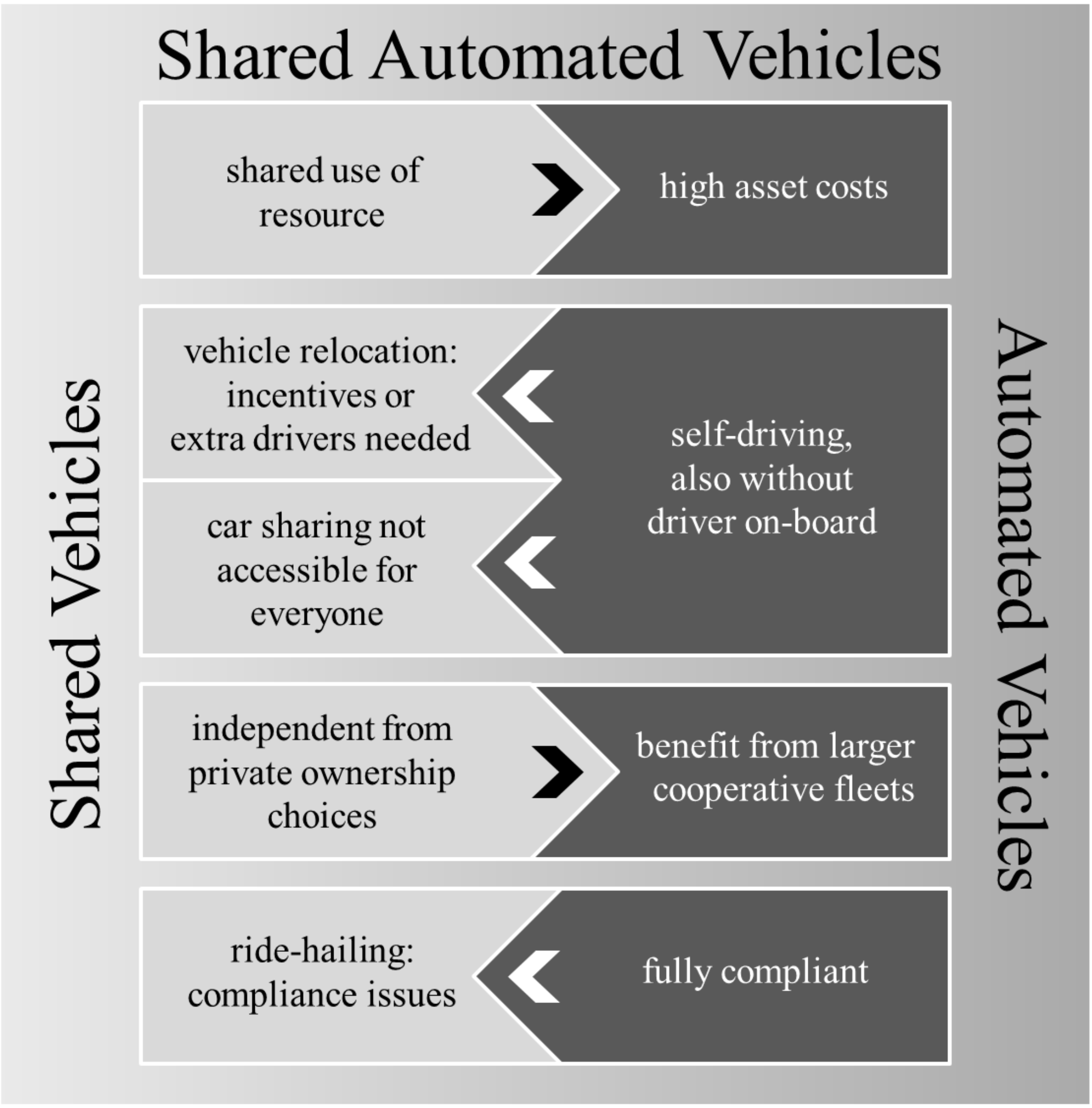


Figure 1.1: Synergies between shared vehicles and automated vehicles when operated as SAV

An example of the issues linked to automated vehicles, which can be overcome by operating them as a shared service, are the high investment costs for such vehicles. Especially in the early phase of selling this new technology, the costs for self-driving vehicles will be substantially higher than for vehicles with lower levels of automation (Regional Plan Association (RPA), 2017; S. Shaheen, 2018; Sperling et al., 2018; Stocker & Shaheen, 2017). This could become a real obstacle to the introduction of self-driving vehicles. What adds up to this is, that current cars have a lifespan of at least 15 years (Litman, 2014), meaning that even decades after the technology for self-driving vehicles comes on the market, there will be still vehicles with no or low-level automation driving around (unless regulation blocks this). The slow start foreseen for fully automated vehicles can be a real hindrance for their success, as they perform best in an environment in which they have to interact as little as possible with road users that are not connected to the information-sharing infrastructure used by self-driving vehicles (Elliott, Keen, & Miao, 2019; Vahidi & Sciarretta, 2018; Ye & Yamamoto, 2019). The success of self-driving vehicles therefore also depends on how fast they can dominate the market and profit from fleet connection and cooperation. This is where the sharing aspect comes into play: by being operated as a shared transport service, the high asset costs of automated vehicles become a minor issue (Stocker & Shaheen, 2017) and by being operated as a public transport service, the replacement cycle for private vehicles also does not play a role anymore. Also updates in the hard- and software of such vehicles are easier to implement if the vehicles are owned by one fleet operator. So by introducing large fleets of SAV, the delicate introductory phase of operating automated vehicles in mixed traffic can be cut short. Furthermore can investment costs for such vehicles decrease when placing large orders for SAV, as economy-of-scale effects come into play and developments in research and production get further stimulated.

The strong synergies between vehicle sharing and vehicle automation allow making the assumption that SAV might become one of the first forms in which we encounter self-driving vehicles (Stocker & Shaheen, 2017). At this point, however, no clear picture can be drawn of what such vehicles would look like, how exactly they would be operated or how we would be using them. Would users be willing to share such vehicles simultaneously? Would their service be operated as a tendered one? Would there be only one centrally dispatched fleet or would there be several fleets operated in direct competition with each other? These and related questions would directly affect ridership for SAV, and thereby could alter our mobility patterns, but also on the longer-term private car ownership levels and spatial needs for mobility services. For this reason, the study of, and preparation for, the possible introduction of such services has recently been put on the agenda of researchers as well as transport authorities and urban planners.

1.2 Planning for Centrally Dispatched On-Demand Transport Services

Transport planning authorities currently have to react to the opportunities and challenges of new on-demand transport services such as ride-hailing or free-floating car sharing (Cetin & Deakin, 2019), and should SAV become a reality, they will have to adapt their policies for such services again. Currently, free-floating car-sharing services are welcomed in many cities around the world. This means that transport planners actively seek contact with providers of such services and often provide benefits in the form of dedicated parking space for the car-sharing vehicles, promotion of the services or even official introduction of such cars as part of the public transport system (Dowling & Kent, 2015; Le Vine & Polak, 2019; S. A. Shaheen, Cohen, & Martin, 2010). Ride-hailing services, on the other hand, are met with more scepticism, as these threaten the established taxi companies and public transport services (Circella & Alemi, 2018; Flores & Rayle, 2017; Hall, Palsson, & Price, 2018) and can cause, if introduced in an unregulated manner, issues in traffic flow (Circella & Alemi, 2018), a decrease in passenger safety (Harding, Kandlikar, & Gulati, 2016) and an increase in overall vehicle-miles travelled (Circella & Alemi, 2018). For this reason, ride-hailing services have been banned or restricted in numerous cases. In other places, however, ride-hailing companies have reportedly been asked to fill the gaps in public transport provision with their transport services in the form of public-private partnerships (Kim, 2019; Span, 2019).

To ensure that the process of introducing SAV is smoother and more sustainable than the one of ride-hailing services, it is crucial to provide planning authorities with information about potential impacts, benefits and issues, as well as indications of how the introduction of such services can be managed and regulated in a beneficial manner. Currently, policymakers and transport authorities are generally not very familiar with on-demand public transport services on a larger scale. Therefore, it can be expected that in an early phase of the introduction of SAV, policies for them will not be all-encompassing. A potential solution to this can be to introduce something policymakers are already familiar with today, namely parking policies (Guerra & Morris, 2018). A further benefit of shaping the introduction of SAV by parking policy is that any efforts taken by a municipality or other planning authority into this direction would also not be wasted if vehicle automation would come much later than expected, or not at all, as it has the potential to be applied to any form of on-demand transport services (Guerra & Morris, 2018).

1.3 Research Objectives and Research Scope

This thesis contributes to the research field that describes and assesses the possible impacts of the introduction of large fleets of shared automated vehicles. The scope of this thesis includes the analysis of user preferences for self-driving vehicles deployed in public transport services, the assessment of relocation strategies which could be used to place idle SAV in the network by fleet manager, as well as the analysis of the effects of dedicated parking management strategies issued by a transport authority or municipality. These aspects are addressed in three separate parts in this thesis, which describe aspects of user preferences, fleet operations and parking management for SAV (Figure 1.2). In particular, the following overarching research questions are addressed:

(1) Who might use self-driving vehicles deployed in road-bound public transport services (automated buses or SAV) and what influences the choices for or against using such services?
(2) What role can relocation of idle vehicles play in the operation of SAV?
(3) How can parking management effectively shape the way SAV perform in our cities?

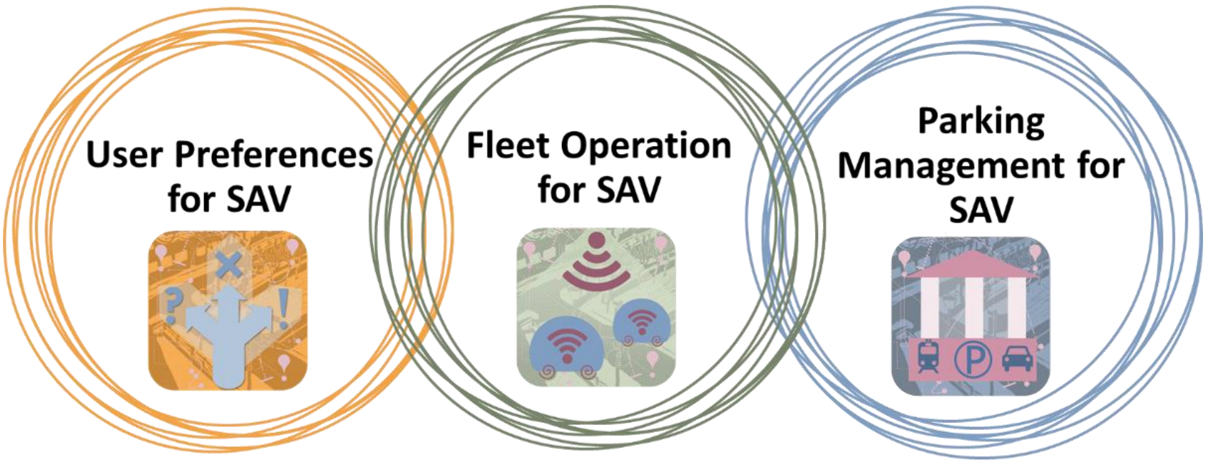


Figure 1.2: Core topics addressed in this thesis: user preferences, fleet operation and parking management for SAV

In this thesis, a scenario is envisioned, in which SAV provide on-demand public transport services for which the following holds: The vehicles are self-driving, so no human intervention is required. The vehicles are sequentially shared, users are thus directly transported from their pick-up location to their destination. The vehicles are centrally dispatched and all vehicles belong to one fleet, which is controlled by one fleet manager. There is hence neither a competitive element between the individual vehicles nor does the fleet manager have to make operational choices regarding competing fleets.

1.4 Research Approach

The research questions posed in the previous section are addressed in three main research steps, for which the following research approaches were applied:

User Preference

(1) To address the first main research question, discrete mode-choice models have been estimated based on data collected in stated-choice experiments featuring automated vehicles employed as public transport services, either in form of self-driving buses or shared automated vehicles. The discrete choice models are estimated as mixed logit models with latent factors and as nested logit models with latent classes. Based on these models, potential user groups can be identified and classified. A more detailed description of the methods applied to determine user preferences for SAV are provided in chapter 2 and chapter 3.

Fleet Operation

(2) To address the second and third main research question, a model which captures the behavioural response to the introduction of a fleet of shared automated vehicles as well as the introduction of parking policies has been developed. This model has been used as the basis of a large-scale agent-based simulation model (using the MATSim framework), which has been deployed and extended for the purpose of analysing relocation strategies for idle SAV, both with and without constraints on parking space. The simulation model has been set up for a case study based on the city of Amsterdam. A detailed description of the model, the case study and the used parameters for the underlying behavioural model is provided in chapter 5.

Parking Management

(3) To address the third research question, a scenario-based analysis of parking policies for shared automated vehicles has been carried out. Based on the model and case study described above, selected parking management strategies are analysed regarding their impact on service efficiency, service externalities and service provision equity (see chapter 6) and briefly compared with the findings for the relocation strategies analysed in chapter 5.

The impact of the service offered by SAV is measured in four main categories:

- Service preference: The preference towards the transport services offered by on-demand self-driving vehicles is measured in regard to the associated costs, waiting times, in-vehicle times and operational parameters such as the presence of a steward.
- Service efficiency and service effectiveness: These aspects are mainly analysed in regard to passenger waiting times and vehicle utilisation rate with respect to empty driven mileage and idle parking.
- Service externalities: The negative externalities are evaluated by total vehicles-kilometres-travelled (VKT) as a proxy for polluting effects and possible safety implications, and by the average driving speed as a proxy for congestion levels.
- Service provision equity: The equity of the service is depicted in the light of passenger waiting time distribution for all users as well as spatially on a zonal level.

1.5 Main Contributions

In this section, the main scientific and societal contributions of this thesis are briefly highlighted.

1.5.1 Scientific Contributions

(1) *Estimating a discrete choice model capturing the choice between regular buses and automated buses* (chapter 2): the model suggests that current users of public transport services are not inclined to switch to automated buses if these do not substantially improve the provided service. In this particular case, the study participants did neither appreciate surveillance measures in the automated bus nor did they prefer the automated bus being operated in a demand-responsive manner. These findings stress the importance to learn more about attitudes towards new modes, and how these might change over the course of time.

(2) *Estimating a discrete choice model capturing the choice between, among others, taxis and SAV* (chapter 3)*:* including taxis to the choice set that also includes SAV allows to directly distinguish between the influence of vehicle automation for SAV and the demand-responsive properties of the service offered by SAV. This set-up helps to gain more understanding of the perception of the properties linked to the service operation and properties of the vehicles themselves.

(3) *Assessing vehicle relocation heuristics simulated for SAV, and how their performance is analysed* (chapter 4 and chapter 5): This assessment shows the impact vehicle relocation can have on the performance of vehicle dispatching, as well as on vehicle-kilometres-travelled. It furthermore reveals that the scientific discussion of vehicle relocation mainly centres around service efficiency, neglecting in parts service externalities as well as service equity.

(4) *Holistic analysis of vehicle relocation heuristics for SAV* (chapters 4, 5 and 6): Various relocation strategies are formulated, simulated in an agent-based model and analysed in regard to the service efficiency and effectiveness, its external effects and service provision equity. Looking at the outcome of simulation studies in regard to these diverse indicators allows drawing a more complete picture of the impact of idle vehicle relocation and vehicle parking.

1.5.2 Societal and Practical Contributions

(1) *Identifying user classes and potential early adopters of automated on-demand transport services among commuters* (chapter 2 and 3): Identifying these groups can be useful for developing business strategies for companies interested in providing transport services operated with automated vehicles.

(2) *Quantifying the necessary price drop or speed gain for automated buses to be more popular than current buses* (chapter 2): These break-even points are determined by applying the estimated discrete choice models to the collected data set. This can support the formulation of operational goals for potential transport services using automated buses.

(3) *Comparing re-active and pro-active relocation strategies for SAV in regard to service effectiveness and efficiency* (chapters 4 and 5): This comparison indicates that operators of on-demand transport services, operated with automated vehicles or not, are well-advised to spread out idle vehicles through the network. In regard to increasing service efficiency, and in some cases even in regard to reducing average passenger waiting times, this strategy outplays those solely relying on demand-anticipation.

(4) Determining the impact of parking management strategies for SAV on their service performance (chapter 6): Spreading idle vehicles throughout the network can also be achieved by restricting dedicated parking facilities. The impact of such parking management strategies is analysed in a holistic way, showing how parking policies for SAV could potentially impact the performance of such on-demand transport services, as well as external effects and aspects of service provision equity. Such analyses can empower transport authorities or municipalities to take a more active role in shaping the role SAV can play in the urban transport system.

1.6 Outline of the Dissertation

The thesis is based on five papers, which are grouped into three main sections, as shown in Figure 1.3, each addressing one of the aspects shown in Figure 1.2. Part I, consisting of chapters 2 and 3, analyses mode choice behaviour in an era of on-demand public transport services. Part II, consisting of chapters 4 and 5, sheds light on the role of vehicle relocation in the operation of a fleet of SAV. Part III, consisting of chapter 6, proposes parking management strategies that can be applied to SAV in order to strengthen its efficiency while guaranteeing sufficient service provision equity as well as containing negative externalities of the service. Finally, findings are summarized and discussed in the concluding chapter. A visualisation of this structure is shown in Figure 1.3. In the following, a brief summary of each chapter is given.

Chapter 2: Taking the Automated Bus: A User Choice Experiment

Based on:
Winter, K., Wien, J., Molin, E., Cats, O., Morsink, P., van Arem, B. (2019). *Taking the Automated Bus: A User Choice Experiment*. 6th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems, MT-ITS 2019 - Proceedings

In this chapter, a first step is taken towards determining who might be the early adaptors of on-demand public transport service operated by buses. On the occasion of a pilot study conducted in the border region between Germany and the Netherlands with automated buses, a mode choice experiment has been conducted among regular public transport users in both countries. Based on this, a discrete choice model was estimated, which includes the captured attitudes of the participants towards trusting automated vehicles as well as their general interest in technology. This chapter highlights the interrelations between the specifics of the service operation and the acceptance of the service.

Chapter 3: Identifying User Classes for Shared Mobility Services

Based on:
Winter, K.; Cats, O.; Martens, K.; van Arem, B. *Identifying User Classes for Shared and Automated Mobility Services*. Under Review.

The insights on the interrelation between the mobility service and the mobility choices are further strengthened in this chapter by presenting a second discrete choice model, which includes, among others, the choice options between free-floating car-sharing, SAV, and taxi. While these transport modes have similar characteristics in the way they are operated, they are perceived differently by potential user groups. The estimated model is primarily used to distinguish the potential early adopters of SAV. The formulation of the behavioural model used for the simulation of a transport service operated by SAV in the following part draws on the insights gained in this chapter.

Chapter 4: Impact of Relocation Strategies for a Fleet of Shared Automated Vehicles on Service Efficiency, Effectiveness and Externalities

Based on:
Winter, K., Cats, O., Martens, K., van Arem, B. (2017). Impact of Relocation Strategies For a Fleet Of Shared Automated Vehicles On Service Efficiency, Effectiveness and Externalities. 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems, MT-ITS 2017 - Proceedings

In the second part of the thesis, the focus is put on the operation of SAV, in particular how the relocation of idle vehicles can strengthen the efficiency and effectiveness of the service they provide. In this chapter, the model used to simulate the service operation of SAV, as well as the model capturing the users' response towards the performance of the SAV, is first introduced. For a small grid network, various relocation strategies for idle vehicles are tested. In this stage, no parking constraints or regulations are applied yet. This small-scale experiment, testing vehicle relocation strategies, provides initial evidence that positioning idle vehicles close to demand hot-spots is outperformed by strategies spreading out vehicles more evenly in the network. This finding strengthens the notion that regulating SAV can be beneficial not just for the users, but also for the service provider.

Chapter 5: Relocating Shared Automated Vehicles Under Parking Constraints: Assessing the Impact of Different Strategies for On-Street Parking

Based on:
Winter, K., Cats, O., Martens, K., van Arem, B. Relocating Shared Automated Vehicles Under Parking Constraints: Assessing the Impact of Different Strategies for On-Street Parking. Under Review.

What has been applied on a small scale in the previous chapter is confirmed for a much larger case study based on the city of Amsterdam in chapter 5. In this chapter, the relocation strategies are simulated in a network with limited parking facilities, now bringing into play the same constraints on parking space we see in the real world. The analysis of the service performance is extended in this chapter by including service provision equity. This holistic analysis serves as a basis for the parking management strategies devised for SAV in the following chapter.

Chapter 6: Parking Space for Shared Automated Vehicles: Why Less Can Be More

Based on:
Winter, K., Cats, O., Martens, K., van Arem, B. Parking Space for Shared Automated Vehicles: Why Less Can Be More. Under Review.

In this chapter selected dedicated parking management strategies for SAV are formulated and simulated. Encouraged by the finding from the previous chapters, that unregulated positioning of idle vehicles close to demand hot-spots is undesirable, the parking restrictions are formulated in such a way that they counteract demand-anticipatory relocation. It is shown that parking management can be a robust means to improve the performance of SAV, reduce undesired externalities and improve the service provision equity, both on a city-wide level, as well as for specific areas in the city. However, a comparison between the intrinsic formulation of relocation strategies as simulated in the previous chapters and the externally imposed parking management measures discussed in this chapter shows, that the former is more effective.

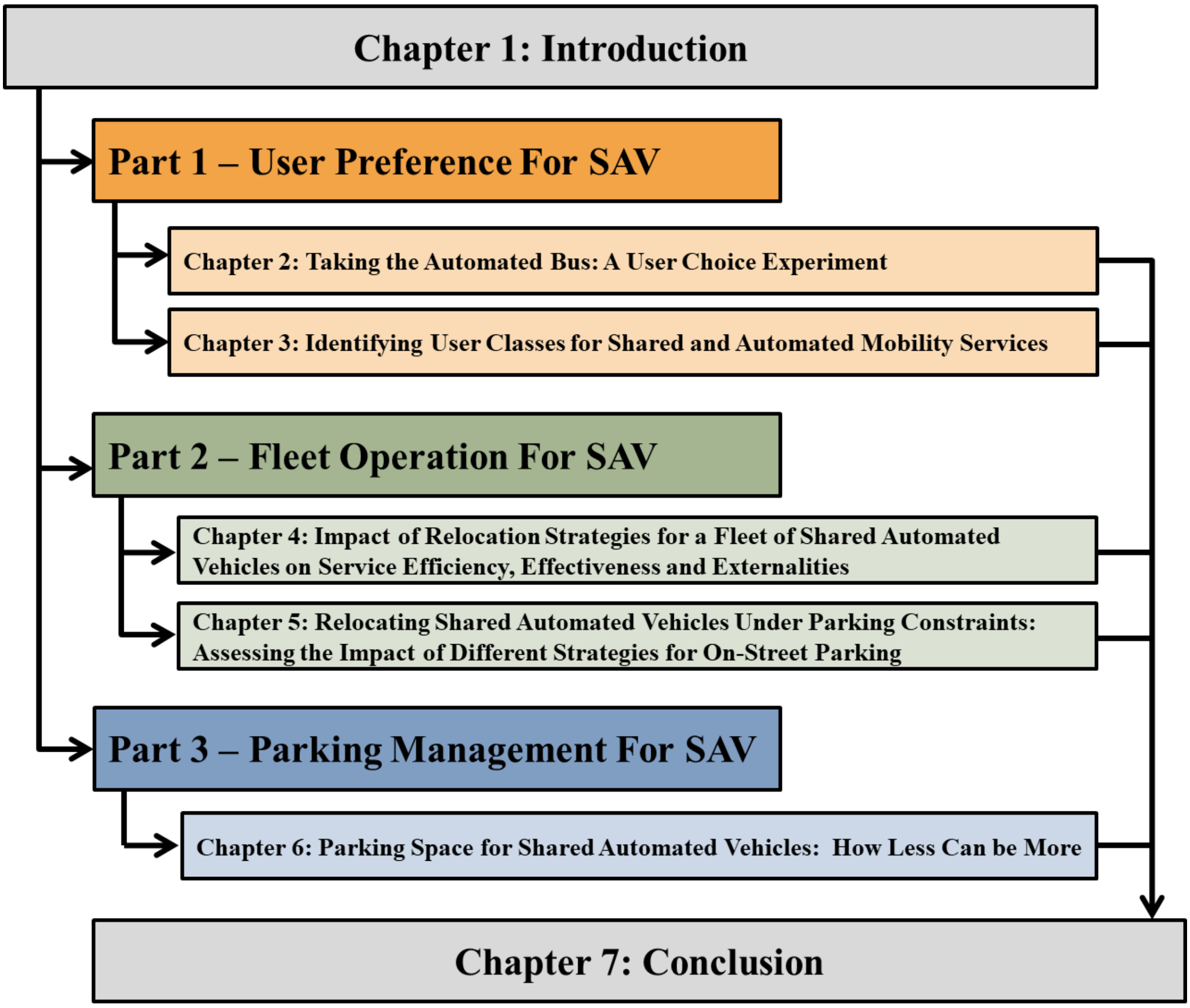


Figure 1.3: Structure of the dissertation

Part I – User Preferences

People's travel behaviour can be described as a series of choices: Where do I want to go? When do I want to leave here? When do I want to arrive there? Which mode of transport do I want to use? Which route shall I choose? Normally we are not making all these choices consciously every time we take a trip, as over time we develop preferences and habits that effectively reduce our perceived choice set to a limited number of options. We tend to travel the same way every time, especially for trips we perform often, such as commuting to work or heading out for our daily shopping. Analysing user preferences for SAV today can provide insight into what new habits might be formed if new transport options provided by such vehicles are introduced in the future.

In this part of the thesis, we determine to what degree automated vehicles providing public transport services could become the preferred options for such habitual trips. In particular, we focus on the mode choice preferences of commuting trips in two specific situations:

(1) automated buses providing partially on-demand transport service in a suburban context (Chapter 2) and
(2) shared automated vehicles operating fully on-demand in an urban environment (Chapter 3).

We described what kind of services such vehicles could provide and asked people about their preferences towards such services by conducting surveys. Based on these stated-preference experiments, discrete choice models are estimated, which can be used to characterize the possible mode choice behaviour in an era when automated vehicles are employed for public transport services.

Chapter 2 - Taking the Automated Bus: A User Choice Experiment

This chapter is based on: Winter, K., Wien, J., Molin, E., Cats, O., Morsink, P., van Arem, B. (2019). Taking the Automated Bus: A User Choice Experiment. 6th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems, MT-ITS 2019 - Proceedings

Abstract

At the brink of the introduction of self-driving vehicles, only little is known about how potential users perceive them. This is especially true for self-driving vehicles deployed in public transport services. In this study, the relative preferences for a trip with a self-driving bus are assessed compared to a trip with a regular bus, based on a stated preference experiment. Based on the responses of 282 respondents from the Netherlands and Germany, a discrete choice model is estimated as a Mixed Logit model including attitudes towards trust in self-driving vehicles and interest in technology. The results show that currently public transport passengers prefer the self-driving bus over the regular bus only for short trips. This is due to the finding that the value of travel time is about twice as high for the self-driving bus as for the regular bus for a short commuting trip. Findings from this study further suggest that the popularity of self-driving buses decreases with the presence of a human steward on-board, or if they are operated as a demand-responsive service with fixed routes. People who currently show a strong interest in technology or trust in automated vehicle technology perceive the self-driving buses better than others. The trust-effect is especially strong for women. In general, men are found to be more inclined to choose the self-driving bus than women. Preferences towards automated public transport services are expected to evolve along with the transition from demonstration pilots to their deployment in regular operations.

2.1 Introduction

Automated vehicles (AVs) are becoming increasingly accessible to the public and first trials with self-driving vehicles are made around the globe. Self-driving vehicles could provide benefits in the efficiency of use of resources, as well as reduced road congestion (Haboucha, Ishaq, & Shiftan, 2017). Furthermore, they might increase the mobility of people without a driver's license and they can contribute to improved road safety (Fagnant & Kockelman, 2015; Haboucha et al., 2017). However, these advantages might lead to increase car travel and consequently to an increase in the total vehicle miles travelled contributing to more congestion (Fagnant & Kockelman, 2015). For this reason, it is important to follow closely the way automated vehicles are employed and used, as only with this knowledge the introduction of automated and self-driving vehicles can be guided successfully.

A concept that could diminish the detrimental effects of an increasing use of motorized vehicles due to vehicle automation could be to use self-driving vehicles to enhance the service on public transport lines or to complement public transport in last-mile solutions (Krueger et al., 2016b; Nordhoff, van Arem, & Happee, 2016). In addition, by introducing self-driving pods or buses, public transport services could provide more flexible on-demand services, as the costs of operating such services are expected to be considerably lower when operated by self-driving vehicles.

User demand for the self-driving vehicle is a prerequisite for its successful implementation (Nordhoff et al., 2016). Currently, travellers do not seem to embrace self-driving vehicles yet (Haboucha et al., 2017; Yap, Correia, & van Arem, 2016). Integrating automated driving and public transport could be key to the development of automated vehicles (Nordhoff et al., 2016). However, only little is known regarding the travellers' preferences and attitudes in regard to self-driving vehicles within a public transport system (Dong, DiScenna, & Guerra, 2017; Krueger, Rashidi, & Rose, 2016a; Nordhoff et al., 2016; Yap et al., 2016).

This study addresses this open research gap by assessing the preferences of public transport passengers in regard to a self-driving bus for an urban commute trip. By having conducted a stated choice experiment, this study sheds light on passengers' preferences towards self-driving buses and how they trade-off travel time and travel cost linked to using a self-driving bus.

The remainder of this paper is structured as follows: in section 2.2, a review on previous stated choice experiments featuring self-driving vehicles is given. In section 2.3, a brief description of the pilot test with a self-driving bus, on which this study is based, is given. The methods used to investigate the public transport passengers' preferences for a self-driving bus is presented in section 2.4. In section 2.5, the conducted survey and the collected sample are discussed. At last, the conclusions and recommendations for further research are presented in section 2.6.

2.2 Literature Review

Complimentary to existing public transport modes, automated vehicles could be deployed as self-driving buses, which could benefit public transport in its efficiency of the operations, traffic safety and lower its costs (Dong et al., 2017).

To be able to assess passenger preferences towards self-driving vehicles, the behaviour of passengers needs to be inferred and analysed. Since self-driving vehicles are currently not a common mode to travel, primary sources of information on passenger preferences are stated preference experiments. In these experiments, observable factors are used which represent attributes describing alternatives, such as travel time and travel costs. An overview of conducted stated choice experiments featuring self-driving vehicles is presented in (F. Becker & Axhausen, 2017; Gkartzonikas & Gkritza, 2019). These overviews, however, do not hold insights on the perception of self-driving buses in particular. In an early stated preference study introducing AV used for public transport services, it has been found that people are in general more worried about larger self-driving vehicles such as self-driving buses than smaller self-driving vehicles, such as self-driving taxis (Schoettle & Sivak, 2014). Findings from stated preference experiments featuring shared automated vehicles (SAV) can therefore not directly be put on a level with preferences for self-driving buses. As there are however only very few studies on specifically the perception of self-driving buses, this literature review includes also findings on AV introduced in stated preference studies in a broader sense.

Past findings on the relative preferences for self-driving vehicles over other modes offer inconclusive and sometimes contradictory results: people were found to prefer self-driving buses over conventional minibuses (Alessandrini et al., 2017), but also have shown to prefer the conventional car and bus over a self-driving vehicle as egress mode (Yap et al., 2016) and rather choose their usual (non-automated) mode over a self-driving vehicle for their reference trip (Krueger et al., 2016b). Looking a bit more into detail into the preferences towards automated vehicles, it has been reported that young people, in particular men and people with a positive attitude towards environmental concerns, tend to be more favourable towards self-driving vehicles (F. Becker & Axhausen, 2017; Gkartzonikas & Gkritza, 2019; Haboucha et al., 2017; Krueger et al., 2016b; Kyriakidis, Happee, & de Winter, 2015; Nazari, Noruzoliaee, & Mohammadian, 2018; Payre, Cestac, & Delhomme, 2014; Piao et al., 2016). Also public transport passengers and people without a car or drivers’ licence are significantly more positive towards shared self-driving vehicles than those currently relying on a private car (Liljamo, Liimatainen, & Pöllänen, 2018; Nazari et al., 2018). Additionally, the preference for self-driving vehicles is strongly influenced by the level of trust in self-driving vehicles (Gkartzonikas & Gkritza, 2019; Nordhoff et al., 2016; Yap et al., 2016). People tend to trust self-driving vehicles in controlled environments more than in mixed traffic (Alessandrini et al., 2017).

In one of the first studies on the position of the self-driving vehicle in the public transport market (Yap et al., 2016), the authors assumed, based on findings in (Fagnant & Kockelman, 2015; Krueger et al., 2016b), that travellers would be willing to pay less for reducing travel time than in conventional egress modes, like the bus. However, they found the willingness to pay for a reduction of in-vehicle time for a self-driving vehicle to be higher than for conventional buses and cars. Reasons for this could be that people might not value the advantage of performing other activities while travelling or that they might feel uncomfortable travelling in a self-driving vehicle because of a lack of trust in the technology (Yap et al., 2016).

These results were contradicted by the findings from a stated preference experiment conducted to explore how people experience a trip with a self-driving vehicle compared to a regular car (Correia, de Looff, van Cranenburgh, Snelder, & van Arem, 2019). In this study, it was found that the value of travel time is lower for a self-driving vehicle with an office interior than the conventional car. This result corroborates the expectations that people are willing to work in a self-driving vehicle (Correia et al., 2019).

Considering trust in self-driving vehicles, the presence of a steward monitoring the bus movements showed a higher intentional usage, suggesting that trust is higher when a steward is present (Dong et al., 2017; Piao et al., 2016). Moreover, the ability to communicate with the bus operator might improve passenger preferences for self-driving buses, for example, with a communication system for information and remote supervision (Dong et al., 2017; Nordhoff, de Winter, Kyriakidis, Van Arem, & Happee, 2018).

Other attitudes that showed a positive effect on the intention to use self-driving vehicles are the perceived convenience of the self-driving bus and a general interest in technology (Correia et al., 2019; Haboucha et al., 2017).

Overall the understanding about if, and under what conditions, people would appreciate the introduction of self-driving buses is very limited. To the best of the authors' knowledge, there is currently no discrete choice model available that features self-driving buses as a mode choice option. In the course of a pilot test with an automated bus, this study presents a discrete mode choice model capturing the choices between a self-driving bus and a regular bus in a situation similar to the one in the pilot region.

2.3 Testing the Self-Driving Bus in a Pilot Study

This study is part of a pilot study testing the implementation of a self-driving bus as a border-crossing public transport service. The pilot study will be set up in the border region between the Netherlands and Germany, connecting the campus of a university in the city of Aachen on the German side and the municipality of Vaals on the Dutch side. The self-driving bus will be operated as a dispatched-on-demand service with a fixed route, allowing passengers to request its service. The pilot study is planned to start in fall 2019 (I-AT Interreg Automated Transport, 2019). The pilot study is a follow-up to the WEpods project conducted in the year 2016 (Winter, Cats, Correia, & van Arem, 2018).

2.4 Choice Experiment and Model Estimation

Since the self-driving bus is currently not a common alternative within the public transport sector, passenger choices cannot be observed yet. Therefore a stated choice experiment has been conducted in order to gain a better understanding of the preferences of public transport passengers in regard to self-driving vehicles, based on which a Mixed Logit discrete choice model is estimated. In the model, attitudes towards self-driving buses are included.

2.4.1 Choice Experiment: Trip Purpose, Mode Alternatives and Their Attributes

For this study, a hypothetical commuting trip from home to a work or study location is described in the choice experiment. For this trip, respondents can choose between three mode alternatives: (1) The first alternative describes a regular bus service, based on the current bus services available in the region of the planned pilot described in section 2.3. (2) The second alternative is a self-driving bus, differing from the regular bus only in not having a driver and being small in size, and thus having fewer seats. (3) The third option is an opt-out alternative, which was added in order to increase the realism of the experiment. The opt-out option is phrased as "I would choose for another alternative", and thus represents any alternative the respondent can imagine beyond the previous two alternatives.

The regular and self-driving buses are described by the attributes travel time, travel costs and waiting time. The presented attribute levels were based on the current bus line operating in the pilot area and represent a bus trip of approximately 3 kilometres in a (sub-)urban area. Two additional attributes for the self-driving bus are considered: (1) 'Surveillance and information' pertains to the presence of either a steward, an interactive screen for communication with the bus operator and a visualisation of what the sensors and cameras of the self-driving bus are detecting, or no extra surveillance. (2) The attribute ‘Service’ defines the operation of the self-driving bus either as a scheduled service or an on-demand service with fixed routes. Table 2.1 provides an overview of the attributes and attribute levels considered in the stated choice experiment.

Table 2.1: Overview of Attributes and Attribute Levels

Travel time	***Travel costs***	***Waiting time***	***Surveillance & Information***	***Service***
7 min	€1,00	2 min	Standard	Scheduled
10 min	€1,60	4 min	Interactive screen	On-demand
13 min	€2,20	6 min	Steward	--
16 min	€2,80	8 min	--	--

2.4.2 Choice Set

The design of the choice sets is based on an orthogonal fractional factorial design, derived with the software NGENE (ChoiceMetrics, 2018). This design allows selecting a subset of all possible choice situations. The design features 24 choice sets, which are blocked in four blocks. Each respondent is thus faced with six choice sets.

2.4.3 Attitudes

To explore if attitudes towards the self-driving vehicle influence the choices made by the respondents in this experiment, a set of attitudinal statements has been included in the survey, see Table 2.2

Table 2.2: Statements Included in the Survey

Variable	**Trust in self-driving vehicles**
TRUST_1	I believe a self-driving vehicle would drive better than the average human driver.
TRUST_2	I am afraid that the self-driving vehicle will not be fully aware of what is happening around it.
TRUST_3	I think that the self-driving system offers more safety than manually driving.
TRUST_4	I would entrust the safety of a close relative to a self-driving vehicle.
TRUST_5	I think that the self-driving bus is only safe when a steward is present.
Variable	**Technology interest**
TI_6	I try new products before others do.
TI_7	I am excited by the possibilities offered by new technologies.
TI_8	I have little to no interest in new technology.
TI_9	New technologies create more problems than they solve.
Variable	**Convenience**
CONV_10	Self-driving vehicles will make life easier.
CONV_11	The best part of the self-driving bus is that it can be requested on demand.
CONV_12	I think that using the self-driving bus is more convenient than using regular buses.
Variable	**Vehicle characteristics**
CHAR_13	I would feel more comfortable in a self-driving bus with several passengers than with a few passengers.
CHAR_14	An interactive screen is a good replacement for a bus employee in the self-driving bus.
CHAR_15	I would feel more comfortable in a self-driving bus than in a regular bus.

The respondents were asked to rate their level of agreement with these statements using a five-point Likert scale. The provided statements are derived from variables that were found to significantly influence the choice behaviour in regard to self-driving vehicles in previous research (Haboucha et al., 2017; Madigan et al., 2016; Payre et al., 2014). Based on the statements, attitudinal factors are formulated, which are included in the model as described in the following. The attitudinal factors are incorporated as mean sum scores for each individual into the discrete choice model.

2.4.4 Specification of the Mixed Logit Model

Based on the results from the stated choice experiment and the determined attitudinal factors, a discrete choice Mixed Logit model is estimated. From the various models estimated, only the one with the highest explanatory power is hereby presented. The model describes the perceived utility U_i of a mode alternative i, which is described in equation 2.1. This model includes β_x, which is the vector estimating the taste parameters associated with the attributes of alternative i and x_i, which is a vector that contains the attribute levels of alternative i. In addition, β_τ is the vector that reflects the importance of the socio-economic variables τ_s of individual s.The model also includes factors representing the respondents' attitudes, as described in the previous section. Mean sum scores represent the attitudinal factors for each individual s and are represented by the vector φ_s, which contains the parameters that estimate the marginal utility of the attitudinal factors. Finally, ε_i is the independent and identically distributed (i.i.d.) error term capturing the unobserved part of the utility U_i.

$$U_i = \beta_x x_i + \beta_\tau \tau_s + \beta_\varphi \varphi_s + \varepsilon_i \tag{2.1}$$

2.4.5 Model Application

Based on the estimated discrete choice model, the choice probabilities for the collected sample are approximated in a model application. For this, a Monte Carlo simulation based on 1000 draws from the estimated distributions for the estimated values for travel time and travel costs is performed. This approach is not interpreted as a forecast for a future modal split, but is rather used for determining the threshold values for travel times and travel costs for the self-driving bus in order to become a competitive alternative to the regular bus.

2.5 Results and Discussion

2.5.1 Sample Description

The survey was distributed through several online platforms, both in Dutch and German. In particular, citizens from the pilot region were invited to participate on the website of the municipality of Vaals and the municipality of Aachen. In total, the answers of 282 participants are included for the model estimation. See Table 2.3 for an overview of the sample characteristics in detail. All respondents use public transport at least once a year, with a share of 71.6% using public transport every week. In regard to the gender of the public transport passengers, the sample is comparable with the Dutch and German average of public transport passengers (Bundesministerium fuer Verkehr und digitale Infrastuktur, 2018; Centraal Bureau voor de Statistiek (CBS), 2018b). Young people and people with higher education are overrepresented compared to the Dutch and German average general population. This has to do with the primary respondent groups targeted with the survey, namely students and employees of the university campus in Aachen, who are commuting between the municipality of Vaals and the campus. Having captured many students also explains the overrepresentation of people with a low income.

Table 2.3 Sample Characteristics

Socio-economic variable	***Category***	***Sample [in %]***
Gender	Female Male	48.9 51.1
Age	18 - 24 years 25 - 34 year 35 - 49 year 50 - 64 year > 64 year	37.2 39.4 13.1 9.9 0.4
Education	Low Middle High	1.1 8.5 90.4
Employment	Full time Part time Student Jobless Retired	45.0 16.7 36.2 1.8 0.4
Income	< € 10.001 €10.001 - €20.000 €20.001 - €30.000 €30.001 - €40.000 €40.001 - €50.000 > € 50.000 No information	30.1 7.8 20.9 13.8 8.5 6.7 12.1
Public Transport Usage	(almost) Every day 5 days a week 4 days a week 3 days a week 2 days a week 1 day per week A few times per month One time per month A few times per year	15.6 16.0 13.1 11.0 11.0 5.0 11.7 5.7 11.0
Country of Residence	The Netherlands Germany	84 16

2.5.2 Factor Analysis

From the responses to the statements shown in Table 2.2, attitudinal factors are derived by performing an exploratory factor analysis. With the factor analysis, the statements are grouped based on the underlying pattern of correlations within the statements. This allows reducing the number of variables introduced to the choice model by replacing the full set of statements with a few factors that explain most of the observed variance. The results of the factor analysis are shown in Table 2.4.

The factor analysis has been performed step-wise, resulting ultimately in a 2-factor solution, incorporating 10 out of the original 15 variables. The other five variables were excluded, as they showed a communality lower than 0.25 and factor loadings of less than 0.5. A simple structure for the factors is reached by performing a VARIMAX rotation. A similar outcome is found for a skewed rotation. However, the interpretability of the VARIMAX rotation and its replicability make this rotation the preferred one and is thus selected in this case.

Table 2.4: Estimation results rotated factor matrix (Factor loadings <0.3 are not shown)

Variable	***Factor 1: "trust in self-driving vehicles"***	***Factor 2: "interest in technology"***	***Communality***
TRUST_3	0.791	--	0.663
TRUST_1	0.742		0.577
TRUST_4	0.716		0.562
TRUST_2	0.670		0.485
CHAR_15	0.578		0.416
TRUST_5	0.506		0.303
TI_7	--	0.916	0.898
TI_8		0.658	0.442
TI_6		0.498	0.329
TI_9		0.451	0.250

The first of the derived factor can be described as *'trust in self-driving vehicles'*, as it includes variables that describe attitudes towards safety and performance of the self-driving bus. The leading statement for this factor is "I think that the self-driving system offers more safety than manual driving". The second factor describes the general *'interest in technology'* of the respondents, dominated by the statement "I am excited by the possibilities offered by new technologies". The variables TI_6 and TI_9 have low factor loadings (below 0.5). However, they are included in the second factor as they fit the interpreted factor and do not have high double loadings. The reliability of the extracted factors is analysed in regard to how close the variables of one factor are related, indicated by the tau-equivalent reliability (Cronbach's alpha). The factor *'trust in self-driving vehicles'* has a value of 0.84, the factor *'interest in technology'* has a value of 0.75, therefore both factors have a high internal consistency.

2.5.3 Discrete Choice Model

The best discrete choice model for the collected sample is derived by estimating a Mixed Logit model correcting for panel effects, including a nesting effect for the two buses and taking possible taste heterogeneity into account for the alternative specific constants and the travel time parameters. The model is estimated with 1000 Halton draws from a normal distribution, which gives stable parameter results. Table 2.5 shows the estimation results of the discrete choice model.

Unobserved Factors

A significant nesting effect is found in the estimation (σ *nesting effect* = -4.88 [$p < 0.01$]), implying that the self-driving bus and regular bus have common unobserved factors in contrast to the third alternative, representing all other possible travel options combined.

The alternative specific constants of the regular bus *Constant REB* (11.8 [p < 0.01]) and self-driving bus *Constant SDB* (10.2 [p < 0.01]) show that the bus alternatives are preferred over the option to choose any other mode. The difference between *Constant REB* and *Constant SDB* is statistically not significant, which indicates that there is no difference in the unobserved preferences within the population based on the data. The standard deviations for the alternative specific constants, however, show that there is significant individual specific taste heterogeneity in the perceived utility of the self-driving bus and the regular bus. The standard deviation (σ *constant SDB* = 0.71) is significant for the self-driving bus with p-value < 0.01. The standard deviation of the regular bus (σ *constant REB* = 0.57) is also considered significant with a p-value of 0.07.

Table 2.5: Estimation results discrete choice model

Parameter	***Mixed Logit model with nesting effect and taste heterogeneity***	***p-value***
σ nesting effect	-4.88 ***	0.00
α_i		
Constant REB	11.8 [10.7, 12.9] ***	0.00
Constant SDB	10.2 [8.8, 11.6] ***	0.00
σ constant REB	0.57 *	0.07
σ constant SDB	0.71 ***	0.00
β_x		
Travel cost REB	-1.8 ***	0.00
Travel cost SDB	-2.08 ***	0.00
Travel time REB	-0.15 [-0.27, -0.04] ***	0.00
Travel time SDB	-0.37 [-0.46, -0.27] ***	0.00
σ travel time REB	0.06 ***	0.00
σ travel time SDB	0.05 ***	0.00
Waiting time REB	-0.26 ***	0.00
Waiting time SDB	-0.19 ***	0.00
DRT service SDB	-0.37 **	0.02
Steward SDB	-0.30 **	0.01
Interactive SDB	0.04	0.68
β_τ		
Female REB	0.74 **	0.04
PT every month SDB	0.22	0.14
Pilot provinces SDB	0.07	0.51
β_φ		
Tech. interest (TI) SDB	0.35 **	0.04
Trust in AVs SDB	0.96 ***	0.00
Female TI SDB	-0.11	0.41
Female AV trust SDB	0.40 ***	0.01
No. parameters	23	
Initial log-likelihood	-1858.85	
Final log-likelihood	-964.39	
Adjusted ρ^2	0.469	

*** = significant at a 99% CI; ** = significant at a 95% CI; * = significant at a 90% CI;
[..] interval estimate from standard deviation σ;
REB = Regular bus; SDB = Self-driving bus

Travel Time and Travel Cost

The marginal utility of the travel cost for the self-driving bus (-2.08 [p = 0.0]) is more negative than for the regular bus (-1.8 [p = 0.0]). The mean parameter for the marginal utility of travel time on a self-driving bus (-0.37 [p < 0.01]) is significantly more negative than the one for the regular bus (-0.15 [p < 0.01]). This means that the time spent while travelling in a self-driving bus has a lower perceived utility than time spent travelling in the regular bus. The standard deviations for the mode-specific travel times are significantly different from zero. This means that there is individual-specific taste heterogeneity for travel times. Based on the parameters for travel time and travel costs, the value of travel time (VOTT) is estimated, which reflects the willingness to pay for travel time reduction. For the regular bus, a mean VOTT of €5.13 per hour is estimated, the one for the self-driving is €10.59 per hour (see Table 2.6). These two values lie in the expected range, given that the current VOTT for travelling in a regular bus in the Netherlands ranges between €7.75 and €10.50 per hour (Kouwenhoven et al., 2014). The results for the VOTT values show that respondents would pay more than double the marginal costs for reducing marginal in-vehicle time spent in a self-driving bus in comparison to a regular bus. This result is in line with findings on how much people would pay for savings in marginal in-vehicle time for public transport in comparison to self-driving vehicles as egress modes (Haboucha et al., 2017; Yap et al., 2016).

Table 2.6: VOTT estimates and Standard Deviations [€/hour]

Alternative	***Mean VOTT [per hour]***	***Standard deviations VOTT [per hour]***	***95% confidence interval***
Self-driving bus	€ 10.59	€ 1.38	[€ 7.87, € 13.30]
Regular bus	€ 5.13	€ 1.94	[€ 1.32, € 8.94]

Waiting Times and Service Specifications

Waiting time for the self-driving bus (-0.19 [p < 0.01]) is valued less negative than the waiting time associated with the regular bus (-0.26 [p < 0.01]). The disutility of waiting time is perceived about four times larger than the disutility for travel times. The interpretation of the values for waiting time for the self-driving bus is however difficult, as it combines the waiting time for the schedule-bound service and for the demand-responsive service. Understanding how passengers perceive waiting times for flexible dispatching transport services will be an important step for implementing these kinds of services successfully.

The on-demand service decreases the perceived utility of the self-driving bus (-0.37 [p < 0.05]), travellers prefer a scheduled-based service over the flexible one. An explanation for this observation could be that an on-demand service requires the extra effort of the traveller, who has to actively send a request in order to make use of the service. This finding is specific to the formulation of the route-based demand-responsive service and does not allow drawing conclusions on the perceived utility of fully flexible services.

Surveillance on the Self-Driving Bus

Regarding the surveillance present in a self-driving bus, respondents prefer to have no extra surveillance on-board the self-driving bus. The presence of a steward is found to reduce the perceived utility (-0.30 [p < 0.05]), whereas the interactive system is not significantly different from zero (0.04 [p=0.68]). This outcome contradicts the findings reported in previous studies (Dong et al., 2017; Piao et al., 2016). The differences in outcome may be caused by the way data has been gathered: in this study, surveillance was presented as one attribute among other attributes such as travel times and travel costs, while in the previous studies respondents were directly asked about their preferences for using a self-driving bus with or without an employee present. This could be an indication that in the trade-offs made during the choice processes captured in this study, surveillance is regarded as less important compared to the other attributes and therefore has a lower impact on the choices made. It could also be that the respondents might not have understood the attribute, as it is part of an unfamiliar alternative. In regard to the steward, it could be that the respondents dislike the presence of extra surveillance personnel, as this can cause the feeling of being watched. Another explanation could be that the extra surveillance might be perceived as a compensation for possible unreliable technical shortcomings of the self-driving bus. This opens a research gap, which is particularly relevant to the success of future trials with self-driving buses and their accompanying policies.

Socio-Economic Factors and Attitudes

A detailed investigation of the results reveals that gender influences the choice made in the experiment. The indicator variable *Female REB* (0.74 [$p < 0.05$]) shows that women have a stronger preference for the regular bus than men. Conversely, it has been shown that male respondents are more likely to opt for the self-driving bus than female ones. This difference between men and women is in line with previous studies that showed that women have a less favourable attitude towards self-driving vehicles than men (Haboucha et al., 2017; Kyriakidis et al., 2015; Piao et al., 2016; Yap et al., 2016). Moreover, the attitudinal factor of *"trust in self-driving vehicles",* which relates to the safety and performance perception of a self-driving bus, has a larger impact on the choices made by women than men. The interaction variable of trust in AVs and gender shows a positive value (0.04 [$p < 0.01$]), indicating that the trust in the automated vehicles has a stronger effect on the preference for the self-driving bus among women than among men.

In regard to the frequency in public transport use, we find that respondents who use public transport services once per month or more perceive the utility of travelling in a self-driving bus higher than those using public transport less frequently. However, the parameter is only significant at the 85% confidence interval, which might be due to the small share of only 11% of the respondents who use public transport services less than once per month. This outcome is in line with previous findings that people who travel with public transport services at least once a month show a more positive attitude towards self-driving vehicles (Liljamo et al., 2018).

Given that the survey with the choice experiment has been distributed often with a link to the upcoming pilot trial, it is tested whether people living within the region where the pilot test will take place have a different perceived utility than those living elsewhere. The parameter that corresponds with the respondents living in the pilot region shows a positive influence on the utility of the self-driving bus (0.07 [$p = 0.51$]), however, it is highly insignificant. Therefore it is concluded that having distributed the survey together with the information that a respondent potentially might be affected by the upcoming pilot trial has not influenced the results significantly. We also find no differences between German and Dutch participants.

Additionally, the general attitude *"interest in technology"* affects the perceived utility of a self-driving bus positively (0.35 [$p < 0.05$]), but less so than the attitude *"trust in self-driving vehicles"* (0.96 [$p < 0.01$]). No significant differences between men and women are found for the factor capturing interest in technology, while the factor capturing trust is influenced by gender. The impact of trust is especially important for women. As can be expected, having generally a high interest in technology and trusting self-driving vehicles have both a positive effect on the choice for a self-driving bus.

Model Application

The estimated values for travel time and travel costs have been used in a Monte Carlo simulation to approximate the choice probabilities for the collected sample based on 1000 draws from the estimated distributions for the results described in Table 2.5. Based on this, the threshold value for travel times and travel costs is determined for two selected scenarios, which are based on the two bus lines currently operating in the pilot region: (1) The “longer trip”, based on a trip with the regular bus which has a fare of € 2.70 and a travel time of 14 minutes. If the self-driving bus would have the same attribute levels, about 28% of the respondents would opt for the self-driving bus and about 57% of the respondents would opt for the regular bus, while 15% would prefer the option to choose any other mode. The break-even point in modal shares between the two buses could be reached by either reducing the fares of the self-driving bus to €2.20 (Figure 2.1a), or reducing its travel time to 11 minutes (Figure 2.1b), while keeping the respective other attribute at the same level as the regular bus. (2) The “shorter trip”, based on a trip with the regular bus which has a fare of € 1.50 and a travel time of 7 minutes. If the self-driving bus would have the same attribute levels, 62% of the respondents would opt for the self-driving bus and 34% would opt for the regular bus, while 4% would prefer the option to choose any other mode. The break-even point in modal shares between the two buses is reached by either increasing the fares of the self-driving bus to €1.90 (Figure 2.1a), or increasing its travel time to 9.2 minutes (Figure 2.1b), while keeping the respective other attribute at the same level as the regular bus.

This application of the model illustrates that in the choice situation discussed in this paper, the self-driving bus is more competitive on shorter trips than on longer ones, which would make it ideal for feeder services or short-distance connections in urban settings. If the self-driving bus is supposed to provide its services also on longer trips, reduced fees would be required in order to turn it into an attractive alternative. Offering such a cost reduction for longer trips is not unrealistic since it is expected that in the future the operating costs of self-driving buses could fall below the ones of regular buses due to reduced personnel costs.

2.6 Conclusion

The aim of this study is to shed light on the preferences of public transport passengers in regard to self-driving buses. A stated choice experiment has been conducted in order to capture the choice behaviour along with certain attitudes towards self-driving vehicles and technology for an urban commuting trip. Based on this experiment, a discrete choice model in the form of a Mixed Logit model is estimated in order to assess the relative preferences.

Overall, it can be concluded that in the specific choice situation presented to the participants, the self-driving bus is preferred over the regular bus only for shorter trips, while the regular bus is preferred for longer trips. Travellers are found to perceive the travel time in a self-driving bus worse than in a regular bus, and thus they are willing to pay more for saving travel time while travelling in a self-driving bus. The value of travel time for the self-driving bus has been found to be more than twice as high as the one for the regular bus.

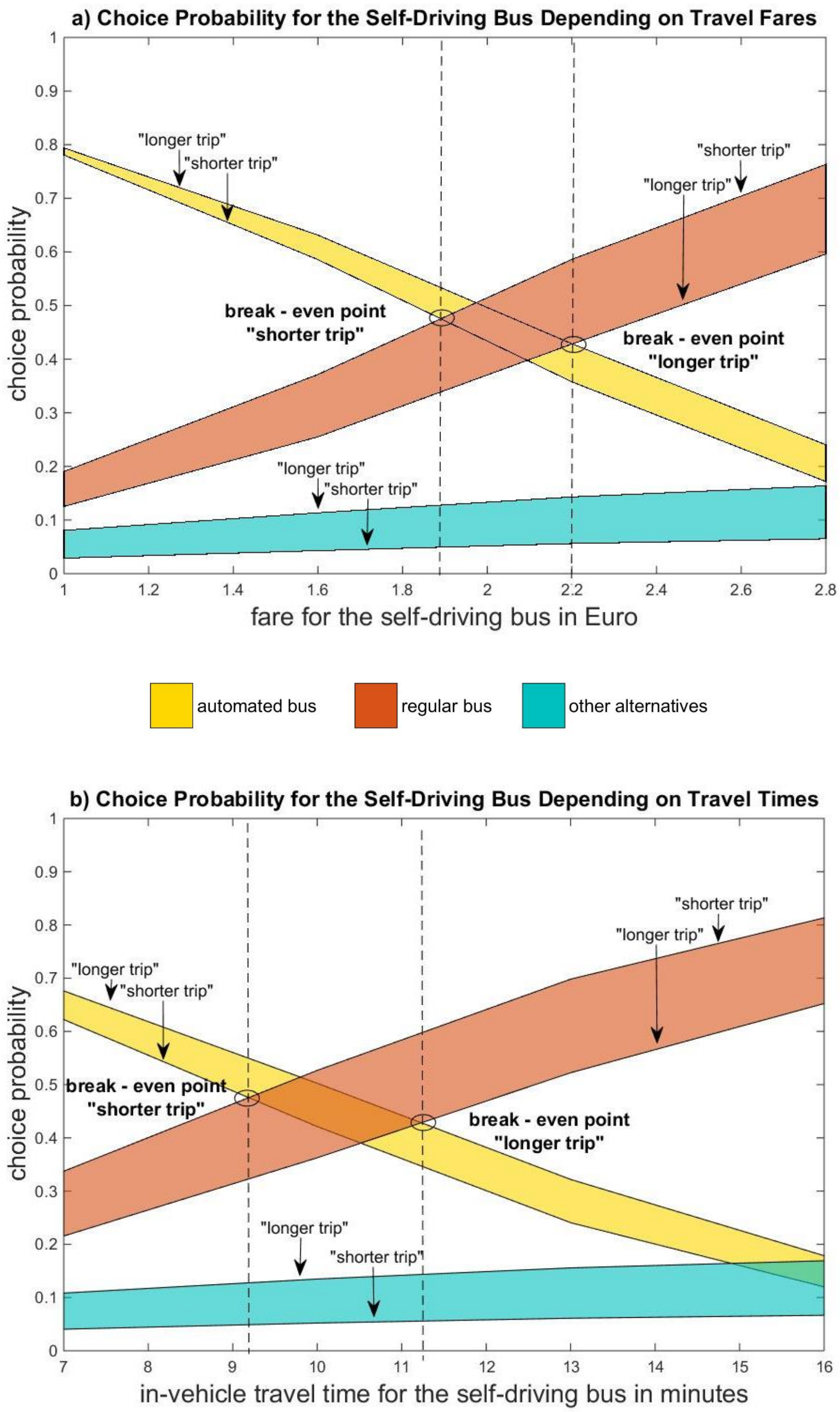


Figure 2.1: Choice probabilities for the automated bus (yellow), regular bus (red) and other alternatives (turquoise) for different (a) travel fares and (b) travel times for the self-driving bus for two scenarios. The break-even points are marked by a dotted line.

Based on the findings in this choice experiment, it can be concluded that in order to increase the perceived utility of travelling in a self-driving bus, the attention has to be given to the following two operational decisions: (1) operating the self-driving bus as a scheduled-based service and not as a flexible dispatching transport service with fixed routes has shown to increase the perceived utility of the self-driving bus and (2) installing an interactive surveillance systems or introducing human stewards onboard has shown to decrease the perceived utility. However, the perception of self-driving buses operating flexibly also in regard to their routes and stop locations has not been examined in this research. Furthermore, the results for the on-board surveillance are not fully in line with the expectations for self-driving buses: It is currently a legal requirement in the Netherlands and Germany to have a steward on board of a self-driving bus and previous studies have shown that passengers are also in favour of a steward being present. That the results of this experiment draw an unexpected picture in regard to demand-responsiveness and on-board surveillance stresses the importance of performing further research into these subjects.

Concerning potential early adaptors and future user groups, it can be concluded that, in general, men have a higher inclination to opt for a self-driving bus than women. Also having a general interest in technology and having a trusting attitude towards self-driving vehicles increases the probability of opting for the self-driving bus over the regular bus. The latter is especially true for women, for whom the influence of the trust attitude is particularly strong. Respondents travelling by public transport services more than once a month also have shown a higher probability of opting for the self-driving bus than those using public transport services less often. To further investigate potential user groups and causal relationships with attitudinal factors, it would be worthwhile to extend the model estimation of the choices for self-driving buses with an integrated choice and latent variable model.

This study is performed at the brink of the start of a pilot test with self-driving buses in the border region between the Netherlands and Germany. The findings from the conducted stated choice experiment allow sharpening our understanding of the preferences in regard to self-driving vehicles used for public transport services. However, it has been shown that in stated choice experiments respondents are inclined to choose for the alternative they are familiar with (Ben-Akiva, McFadden, & Train, 2019), which could have influenced the outcome of the choice experiment featuring the self-driving bus as an unknown alternative. Thus, an even better understanding could be gained by also collecting data from observed choices during the pilot trial and by performing a second stated choice experiment after the introduction of self-driving buses tested in the pilot trial. This would allow detecting any changes in preferences of self-driving buses caused by an increasing degree of familiarity with these kinds of vehicles.

Chapter 3 - Identifying User Classes for Shared and Automated Mobility Services

This chapter is based on: Winter, K.; Cats, O.; Martens, K.; van Arem, B. Identifying User Classes for Shared and Automated Mobility Services. Under Review.

Abstract

New forms of shared mobility such as free-floating car-sharing services and shared automated vehicles have the potential to change urban travel behaviour. In this paper, we identify potential user classes for these new modes. For this, a stated choice experiment on mode choice among a sample of the Dutch urban population has been conducted, which features free-floating car-sharing and shared automated vehicles next to private vehicles, bus, and taxi. The experimental design allows disentangling the effects of vehicle ownership, vehicle sharing, and vehicle automation on the perceived utility of these modes. Latent class choice models were estimated to capture the heterogeneity in these preferences among the respondents. The most explanatory mode choice model is obtained by estimating a 3-class nested logit model capturing the impact of vehicle ownership. The results show that higher educated and more time-sensitive respondents are more inclined than others to favour the (automated) car-sharing options. By simulating a scenario that directly compares car with free-floating car-sharing and taxi with shared automated vehicles, a migration analysis has been performed. This analysis shows that the preferences towards shared automated vehicles and free-floating car-sharing is highest for those currently combining car and public transport for their commute. Commuters using the car showed a high preference towards free-floating car-sharing, in particular as for the latter no parking fees are issued. Respondents currently commuting by public transport showed the lowest preference for the new modes.

3.1 Introduction

The progress in the development of new vehicle technology and digital communication technology is leading to the emergence of new types of vehicles and mobility services. Two drivers of the possible diversification of mobility enabled by these developments are vehicle automation and urban vehicle sharing (Greenwald & Kornhauser, 2019). With the development of vehicle automation progressing rapidly and shared mobility gaining market shares, the question arises how the broad implementation of such concepts may change the transport service landscape. Car-sharing is mainly popular in Europe (S. Shaheen, Bansal, Chan, & Cohen, 2017), while ride-sourcing has considerable growth rates around the globe (Jin, Kong, Wu, & Sui, 2018). Nevertheless, both of these forms of shared mobility are still confined to niche markets and, with the exception of a few locations, are not available in large-scale systems with high coverage or accessibility. For this reason, such services are, so far, mainly used by quite specific user groups: e.g. for car-sharing systems in Europe it has been shown that these are mainly used by young people living in cities, mainly men and people with a higher education level (H. Becker, Ciari, & Axhausen, 2017). Similar characteristics were found for the users of ride-sourcing services (Young & Farber, 2019). These characteristics are often associated with so-called “early adopters” of such new mobility services (Alemi, Circella, Handy, & Mokhtarian, 2018).

How travel behaviour of other groups might change in the light of new shared mobility services available on a large scale remains uncertain, as long as these services do not have high coverage. The primary sources of information on traveller’s choices for these new mobility services are therefore still stated preference experiments. This study contributes to building up a better understanding of the potential migration from the current modes to the new, shared transport services enabled by the developments in digital communication technology. In particular, a mode choice model is estimated that includes current motorized modes as well as *Free-Floating Car-sharing* (FFCS) and *Shared Autonomous Vehicles* (SAV). In contrast to station-based car-sharing, there is no designated infrastructure linked to this form of mobility and users can freely choose their departure time as well as their destination (Ferrero et al., 2018). SAV can be described as a form of FFCS, in which vehicles travel autonomously, i.e. with no driver on board, transporting at least one passenger to its final destination. The required level of driving automation of such vehicles, therefore, has to be level 4 or 5 (SAE International, 2018). For FFCS and SAV, the act of vehicle sharing is a sequential one, as a ride is not shared with unknown passengers. These modes offer therefore the same level of privacy as the private car. SAV bear a resemblance to current taxi services and ride-sourcing services in the way they are operated and are thus also referred to as *autonomous taxis* or *aTaxi* (Greenwald & Kornhauser, 2019).

The number of stated-choice experiments comparing free-floating car-sharing with other motorized modes is not large, and the findings of these studies are not always consistent: while some examples show that older people are more likely to choose one-way car-sharing than younger ones (de Luca & Di Pace, 2014; Yoon, Cherry, & Jones, 2017), shows the majority of stated-preference experiments that it is the younger ones who are most likely to switch to such car-sharing services. As summarized by Spurlock et al. (2019), the most commonly observed user characteristics for shared mobility services are, that they are younger, richer, more educated and have fewer children than the average population.

In the overview of the first stated choice experiments featuring automated vehicles (F. Becker & Axhausen, 2017; Gkartzonikas & Gkritza, 2019), it becomes apparent that only a few of these studies focus on the automated vehicle as a shared mode. In a stated choice experiment conducted among an Australian online panel, sequentially shared and simultaneously shared automated vehicles showed to be perceived as two distinctive modes by the participants, with a strong preference for sequentially shared SAV over simultaneously shared SAV (Krueger et al., 2016b). Conversely, a stated choice experiment conducted among a German online panel found that the simultaneously shared SAV is preferred over the sequentially shared one

(Kolarova, Steck, Cyganski, & Trommer, 2018) – the authors suggest that this could be attributed to the lower costs associated with the simultaneously shared option. In regard to potential early adopters of SAV, the following demographics have been found to describe people with a higher preference for SAV: people currently using public transport or using multiple modes frequently (Krueger et al., 2016b), younger people (Haboucha et al., 2017; Krueger et al., 2016b), men (Haboucha et al., 2017) and people with a higher income or a higher degree of education (Bansal, Kockelman, & Singh, 2016; Barbour, Menon, Zhang, & Mannering, 2019; F. Becker & Axhausen, 2017; Haboucha et al., 2017). In regard to the current commuting behaviour, it has been shown that people currently commuting long distances by car and those who experience usually short parking-search times are less likely to use shared automated vehicles (Barbour et al., 2019).

Estimating mode choice models for mode alternatives that are not widely available or do not exist yet remains a challenge. However, the need for models incorporating shared (automated) mobility services is rising with their rapid introduction. But a conclusive picture on mode choice in the era of (automated) car-sharing cannot be drawn at this point, as any conducted mode choice experiment featuring these mode alternatives is merely a snapshot in time of the current perception of these modes. It remains therefore important to conduct such experiments continuously over time, as well as for the different operational specifications of shared (automated) mobility services, different regions, different trip purposes and combinations of mode choice options. This research contributes to these efforts by conducting a mode choice experiment featuring a combination of shared mobility options that has not been tested so far. The experimental design, detailed in the following section, allows disentangling various features related to new mobility services. The focus of the analysis is put on the differences in mode preference, or taste heterogeneity, in order to identify potential user classes for these modes. Our attention is, in particular, turned to the current mode choice as a predictor.

The remainder of this paper is structured as follows: The methodological specifications of the stated choice experiment are shown in section 2. In section 3, a latent class choice model for mode choice preferences is described and the estimated results are presented and analysed. In section 4, the results are discussed and an outlook on further research needs is given.

3.2 Stated Choice Experiment

In order to determine how mode choice behaviour could change with the introduction of Free-Floating Car-sharing (FFCS) and Shared Autonomous Vehicles (SAV), we conducted a stated choice experiment. For this, an online survey was distributed, using the online survey software Collector. Participants were asked to make a choice between various mode choice options in 9 choice situations. Additionally, socio-economic parameters have been collected on an individual and household level, as well as the participants' familiarity with car-sharing and ride-sourcing services.

3.2.1 Description of the Choice Situation

For the choice experiment, a trip was described as a commuting trip to a fictitious workplace or educational institution in the respondents' home town. The trip distance was set to be approximately 8 kilometres. This is just above the threshold value of 7.5 kilometres, below which the bike is the most preferred mode in the Netherlands and above which more than three-quarters of all trips are performed by car (Ministry of Transport Public Works and Water

Management, 2009). This trip length has been selected in order to be able to analyse the preference of SAV as an alternative to private cars in an urban commute. The choice experiment refers to commuting, as it is an important trip purpose in the Netherlands (and elsewhere), in particular during rush hours (Hoogendoorn-Lanser, Schaap, & OldeKalter, 2015).

In each choice situation, five travel mode alternatives were presented to the participants: privately owned vehicles *(car)*, free-floating car-sharing *(FFCS)*, taxis *(taxi)*, a direct bus line *(bus)* and shared automated vehicles *(SAV)*. Respondents were familiarised with the concepts of FFCS and SAV by providing the descriptions shown in Figure 3.1. They were free to choose any mode option irrespective of their current situation in terms of car ownership and driving license possession.

3.2.2 Design of Stated Choice Experiment

Following the argumentation of Walker et al. (2017), an orthogonal design has been selected as the most suitable layout of the stated choice experiment. The design was generated using 54 choice tasks, blocked in six groups by using the software Ngene. The five mode-alternatives are characterized by six attributes, each with three levels (Table 3.1). The attribute levels in terms of travel time and travel costs were chosen to be similar to travel times and costs Dutch commuters commonly experience.

Table 3.1: Mode Attributes and Attribute Levels as Included in the Choice Experiment

	car	***FFCS***	***bus***	***taxi***	***SAV***
Travel costs [in Euro]	1.2; 2.4; 3.6	1.2; 2.4; 3.6	1.2; 2.4; 3.6	3.6; 4.2; 4.8	2.4; 3.6; 4.8
Parking costs [in Euro]	0; 2.5; 5	N.A.	N.A.	N.A.	N.A.
Access and Egress Time [in min]	2; 4; 6	6; 10; 14	2; 6; 10	N.A.	N.A.
Waiting Time [in min]	N.A.	N.A.	1; 4; 7	1; 4; 7	1; 4; 7
In-Vehicle Time [in min]	15; 20; 25	15, 20, 25	20; 25; 30	15; 20; 25	15; 20; 25
Parking search Time [in min]	1; 4; 7	1; 4; 7	N.A.	N.A.	N.A.

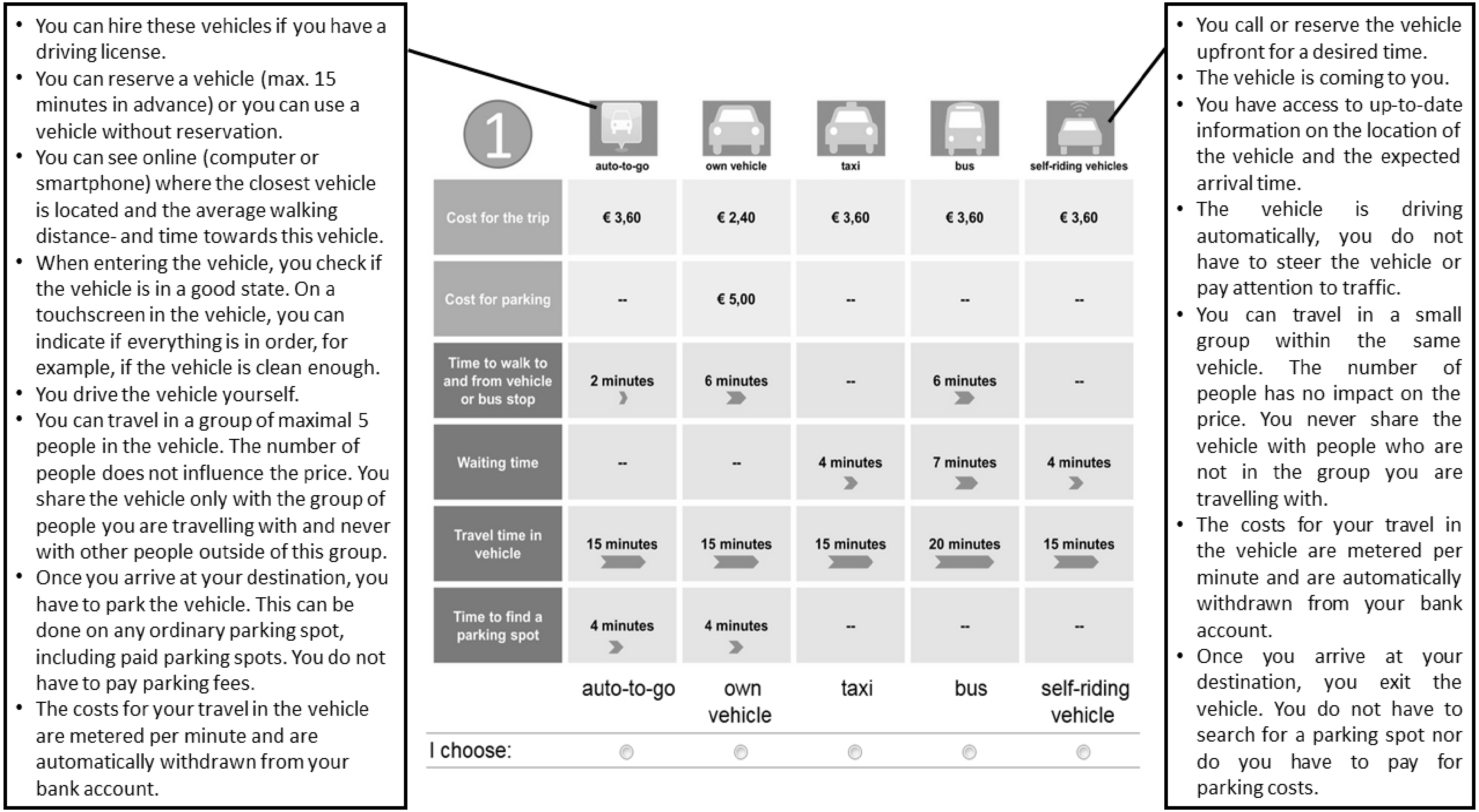


Figure 3.1: Description of FFCS and SAV as presented to the participants (translated from Dutch)

3.3 Results

3.3.1 Description of the Choice Situation

The stated choice experiment has been conducted in April 2016 among 840 members of an online panel (data set available at: http://doi.org/10.4121/uuid:4ac4d7b7-c8b0-42ec-a096-55a4f1837585). The participants were older than 18 years old and originated from the four largest cities of the Netherlands (Amsterdam, The Hague, Rotterdam, and Utrecht). In order to capture the commuting population, only respondents studying or working more than 12 hours per week (employed, self-employed or as volunteers) were included. After excluding inconsistent answers, the final data set has been reduced to 796 responses (95% of the total sample). This sample size is representative of the working population of the four cities, which has a population size of 1,119,300 (Centraal Bureau voor de Statistiek (CBS), 2018b) on a confidence interval of 99% and a margin of error of 5%. The main characteristics of the respondents in this data set are presented in Table 3.2.

Table 3.2: Main Socio-Demographic Characteristics of Respondents

Characteristic	***Total number (percent) [class]***
Respondents:	796
Mean age (standard deviation):	41.78 (14.1)
Respondents per age classes (in percent) [class]:	204 (25.6%) [18-29]; 168 (21.1%) [30-39]; 153 (19.1%) [40-49]; 159 (20.0%) [50-59]; 112 (14.1%) [60-80]
Gender: male; female (in percent):	399 (50. 1%); 397 (49.9%)
Driving license holder (in percent):	684 (85.9%)
Uber user and/or chauffeur (in percent):	97 (12.2%)
Highest level of education (in percent) [class]:	108 (13.6%) [Primary school and lower education]; 317 (39.8%) [High school or mid-level education]; 370 (46.5%) [higher education]
Household with children (in percent):	215 (27.1%)
Household has access to at least one vehicle; and more than one vehicle (in percent):	598 (75.1%); 168 (21.1%)
Yearly household income (in percent) [class]:	191 (24.0%) [0-30,000 Euro]; 321 (40.3%) [30,000-60,000 Euro]; 150 (18.8%) [more than 60,000 Euro]; 134 (16.8%) not reported
Households with at least one household member subscribed to a car-sharing service in general and to a free-floating car-sharing service in particular (in percent):	76 (9.1%) [Car-Sharing in general]; 24 (3.1%) [Free-Floating Car-Sharing]

The distribution of gender, income, and access to at least one vehicle per household are all similar to the Dutch national average (Centraal Bureau voor de Statistiek (CBS) 2016; CBS 2015). The sample distribution does however not represent the national modal share for commuters. Around 60% of all workers commute by private car in the Netherlands (Centraal Bureau voor de Statistiek (CBS), 2018a), while the share of commuters using (partly) public transport lies around 13% (Heinen, Maat, & van Wee, 2013). The findings in the collected sample differ in this, as only 29% of the respondents indicated that they exclusively commute by car, while 35% of the respondents indicated that they commute (partly) by public transport, as shown in Figure 3.2.

Figure 3.2: Commuting modal split of the collected sample (left) and the Dutch average (right)

3.2.3 Mode Choice Model Estimation

We estimated the model as a nested logit model with latent classes. For the mathematical formulation of such a hybrid choice model, we point to the work of Wen et al. (2012). This model has been selected for two reasons: (1) the modes presented in the choice experiment share unobserved attributes and (2) a strong heterogeneity in taste has been observed among the respondents. The implications of this are discussed in the following.

Introducing Nested Logit Models to Account for Shared Unobserved Attributes

To account for unobserved correlations related to the dimensions between the mode alternatives, we estimated nested logit (NL) models for various nesting structures related to car ownership, vehicle automation, the level of privacy in the vehicle, driving tasks and the demand responsiveness of a mode. The lowest log-likelihood values and minimum Bayesian Information Criterion (BIC) values were obtained for the nested logit model taking car ownership into account, corroborating the findings in Haboucha et al., (2017). The log-likelihood ratio test shows a significantly better modal fit on a 99.9% confidence level for this model, and all nest coefficients lie within the required range [0,1]. Conceptually, this model takes into account that the mode option *car* is privately owned, while *FFCS, taxi, bus,* and *SAV* are shared modes.

Introducing Latent Classes to Account for Decision Rule Heterogeneity

In the collected response set, 24% of all respondents selected exclusively one mode throughout all nine choice questions. A large share of respondents showing lexicographic preferences is not an uncommon observation in stated choice experiments with labelled alternatives, especially in the presence of new or unknown alternatives. Comparable stated-choice experiments have shown before that approximately a quarter of the respondents are non-traders (see e.g. Ciari & Axhausen, 2012; Haboucha et al., 2017). Introducing latent classes to the model is an appropriate means to capture non-trading behaviour (Bahamonde-Birke & Ortuzar, 2015).

A three-class model has been selected, based on its fitting statistics and its meaningful and significant nesting and class membership parameters. The class membership is characterized by four categories: age group (below or above 40), education (low and mid-level education or high-level education), currently commuting by private vehicle, and not public transport (true or false) and currently commuting by public transport, and not a private vehicle (true or false). Introducing these nested classes further improves the model fit of the nested logit model on a 99.9% confidence level for the log-likelihood ratio test, and the BIC value of the model with latent classes is significantly lower (Δ-BIC= 442).

Estimated Parameters Values

The nested logit model with latent classes was estimated with the dedicated software BIOGEME (Bierlaire, 2003), using the optimization algorithm "BIO" intrinsic to the software. The estimated parameter values for the panel response set collected from 796 respondents (7164 total number of observations) are shown in Table 3.3. The model consists of 41 variables, has a rho-square value of 0.32 and a final log-likelihood of -7769.

Table 3.3: Estimated coefficients, class membership parameters and nesting parameters

Class *(class-membership probability in %)*	***Class 1 (62.9 %): "Brisk Sharers"***		***Class 2 (20.26 %): "Public Transport Enthusiasts"***		***Class 3 (16.79 %): "Car Captives"***	
Utility Coefficients value [p-value]: *** = significant at 99% CI, ** = significant at 95% CI, * = significant at 90% CI N.A.: not applicable, constrained by specification						
ASC_{FFCS}	1.09	[0.00]***	1.18	[0.00]***	-2.85	[0.00]***
ASC_{PT}	0.816	[0.00]***	1.61	[0.00]***	-2.71	[0.00]***
ASC_{SAV}	1.30	[0.00]***	1.22	[0.00]***	-2.92	[0.00]***
ASC_{taxi}	1.21	[0.00]***	1.23	[0.00]***	-2.63	[0.00]***
$\beta_{cost\_parking}$	-0.272	[0.00]***	-0.278	[0.00]***	-0.127	[0.06]*
β_{cost}	-0.218	[0.00]***	-0.147	[0.03]**	-0.010	[0.40]
β_{walk}	-0.02	[0.00]***	N.A.	--	N.A.	--
β_{wait}	-0.028	[0.00]***	N.A.	--	N.A.	--
$\beta_{IVT,FFCS}$	-0.025	[0.00]***	-0.005	[0.09]*	-0.02	[0.41]
$\beta_{IVT,SAV}$	-0.025	[0.00]***				
$\beta_{IVT,taxi}$	-0.031	[0.00]***				
$\beta_{IVT,bus}$	-0.012	[0.00]***				
$\beta_{IVT,parking\_search}$	-0.011	[0.01]**	-0.068	[0.00]***	N.A.	--
Class Membership value [p-value]: *** = significant at 99% CI, ** = significant at 95% CI, * = significant at 90% CI						
intercept δ	0.00	(fixed)	-0.69	[0.00]***	-1.68	[0.00]***
18 to 39 years old	0.00	(fixed)	-1.28	[0.00]***	-0.992	[0.00]***
high education	0.00	(fixed)	0.11	[0.63]	-0.517	[0.03]**
currently private car for commuting	0.00	(fixed)	-1.79	[0.00]***	1.77	[0.00]***
currently public transport for commuting	0.00	(fixed)	1.09	[0.00]***	-0.65	[0.23]
Nest Coefficients scale parameter [p-value]: *** = significant at 99% CI, ** = significant at 95% CI, * = significant at 90% CI						
μ_1	1.00	(fixed)	1.00	(fixed)	1.00	(fixed)
μ_2	3.91	[0.00]***	6.90	[0.04]**	4.55	[0.37]
The parameter for modes that are not privately owned has a scale parameter of μ_2 = 3.91, leading to a nest coefficient of μ/μ_2 = 1/3.91= 0.26 for Class 1, and to nest coefficients of 0.15 and 0.22 for Class 2 and Class 3, respectively. For all classes, the nest coefficient lies thus between 0 and 1, which is a requirement for a valid nesting structure.						

	Sample Average	"Brisk Sharers" (62.9%)	"Public Transport Enthusiasts" (20.3%)	"Car Captives" (16.8%)
18 to 39 years old	47%	57%	33%	25%
high educational level	47%	50%	44%	37%
commute by private car (and not public transport)	37%	35%	6%	81%
commute by public transport (and not private car)	25%	22%	53%	4%

Figure 3.3: Class membership probability per included socio-economic variable

The probabilities of belonging to a class are distributed in the following way: 63% for Class 1, 20% for Class 2 and 17% for Class 3. In Figure 3.3, the composition of the three classes in regard to the socio-economic categories is shown in comparison to the sample average. The underlying colour scheme indicates the class deviation from the sample average, with red showing an underrepresentation and blue an overrepresentation compared to the sample average within one socio-economic category.

Not just the mode preference, as discussed in section 3.2.2, but also the sensitivity to cost and travel time can be the reason for discontinuous decision making. Respondents who have a larger probability to fall into Class 1 and Class 2 are more cost-sensitive than those with a larger probability to fall into Class 3. By modelling latent classes, these sorts of lexicographic preferences are captured to some extent. Based on these observations and the class mean values, the following class descriptions are made:

- "*Brisk Sharers*" (Class 1): This majority group (57%) prefers shared modes over private cars, as indicated by the strong and positive alternative specific constants (*ASC*) for all shared modes. *Brisk Sharers* show a much stronger sensitivity towards an increase in travel time than *Public Transport Enthusiasts* (class 2). *Brisk Sharers* have a higher likelihood to be younger than 40 years old.

- "*Public Transport Enthusiasts*" (Class 2): This group is the second largest group (20.3%) and represents individuals who currently tend to commute by public transport, and not by private car. They show a higher disutility towards parking costs, but have a lower value of travel time changes and are less sensitive to changes in in-vehicle-time than *Brisk Sharers*. Theyshow an equally strong preference for shared modes in contrast to the private car. *Public Transport Enthusiasts* have a higher likelihood to be older than 40 years old.

- *"Car Captives*" (Class 3): This small group (16.8%) consists of individuals who currently commute by private car. This group shows a strong preference towards the private car in the choice experiment as well, as indicated by the strong negative ASC for all shared modes. *Car Captives* are non-traders who can be characterized as mode-captives favouring private cars. In terms of their socio-economic profile, they tend to be older and less educated than the sample average.

As can be seen in Table 3.3, not all variables presented in the mode choice experiment were included in the final model, in particular the in-vehicle-time for the private car proved to be insignificant, and showed an unexpected positive sign. This variable has been excluded from the model under the consideration that the preference for travelling in private cars is captured in the strong values for the alternative specific constants (ASC) present in all three classes. These indicate that participants disregarded to a certain extent other parameters detailing the trip presented to them in the choice experiment. This is true in particular for the class of the *Car Captives*, for which also the coefficient for the in-vehicle-time and the travel costs are not significant. This class mainly captures respondents with lexicographic preferences making choices irrespective of the attributes and attribute levels, as discussed in the previous section.

Travel Costs and Parking Costs
No significant difference could be observed for the perception of travel costs for the different modes, and therefore the coefficient for the travel costs is modelled as a mode-generic one in all classes. The cost of parking, which only occurred in the case of the private car, is penalized in all three classes stronger than the cost of travelling. This is particularly true for the class of the *Car Captives*, for which this parameter has proven to be the only one out of the parameter set detailing the trip, to significantly have impacted the choices.

Travel Time
In terms of time-related parameters, the *Brisk Sharers* perceive a significant difference between the in-vehicle time for the different shared modes. This class penalizes spending time travelling in the bus the least, followed by the in-vehicle-times in SAV and FFCS, the lowest preference is shown for the in-vehicle time spent in taxis. The strong difference in the preference for SAV and taxi is also present in the alternative specific constants ASC_{taxi} and ASC_{SAV}. This reveals the perception of the utility of vehicle automation in itself, as taxi and SAV have been presented to be equal in regard to the service they provide apart from one being a self-driving vehicle and the other being driven by a taxi-chauffeur. The class of *Brisk Sharers* prefers travelling in the self-driving vehicle, with the difference in preference being mainly captured in the alternative specific constants and thus not only relating to the time spent in the vehicle.

Differing from the other two classes, *the Brisk Sharers* also consider the access/egress walking time and waiting time in their choice, which is in this class generally penalized slightly stronger than the in-vehicle-time spent in the shared modes. For the classes of the *Public Transport Enthusiasts* and the *Car Captives*, a mode generic coefficient for all shared modes proved to be the most descriptive. It is remarkable that, even while the in-vehicle time does not majorly influence the mode choice behaviour of the *Public Transport Enthusiast*, there is a strong aversion towards the time spent searching for a parking spot.

3.3.3 Model Application: Modal Migration Analysis

In order to get a better understanding of the estimated mode choice preferences per class, the model is applied to a specific scenario by simulation (based on 10,000 draws). In this scenario, the attribute levels have been set equal for car and FFCS, as well as for taxi and SAV, to allow a direct comparison between these modes respectively. The applied values are shown in Table 3.4.

The obtained modal shares shown in Table 3.4 are explored in more detail in a migration analysis, showing the choice probabilities itemized for the current commuting modes used by the participants of this study. In figure 3.4, the migration flows are shown from the current modes (left) to the mode choices based on the estimated model applied to the scenario (right). The width of each flow towards a mode is directly proportional to the estimated probability for a commuter group to choose this mode. So it can be seen that the largest contribution to the estimated modal share of private cars stems from commuters also currently using a private car, which have an estimated probability of 30% to choose a private car in this scenario. Similarly, the largest contribution to the estimated modal share of the bus stems from current public transport users, with an estimated probability of 37% of choosing public transport. Respondents indicating that they currently commute by combining private car and active modes (walk, cycle) show the same mode choice probabilities as those indicating to commute only by car.

Table 3.4: Attribute levels applied in the scenario and resulting choice probability per mode

	car	***FFCS***	***bus***	***taxi***	***SAV***
Travel cost [in Euro]	2.4	2.4	2.4	3.6	3.6
Parking cost [in Euro]	0	N.A.	N.A.	N.A.	N.A.
Access/Egress time [in minutes]	6	6	6	N.A.	N.A.
Waiting time [in minutes]	N.A.	N.A.	4	4	4
In-vehicle-time [in minutes]	20	20	20	20	20
Parking-search time [in minutes]	1	1	N.A.	N.A.	N.A.
	↓	↓	↓	↓	↓
Estimated Choice Probability	24%	21%	25%	14%	16%

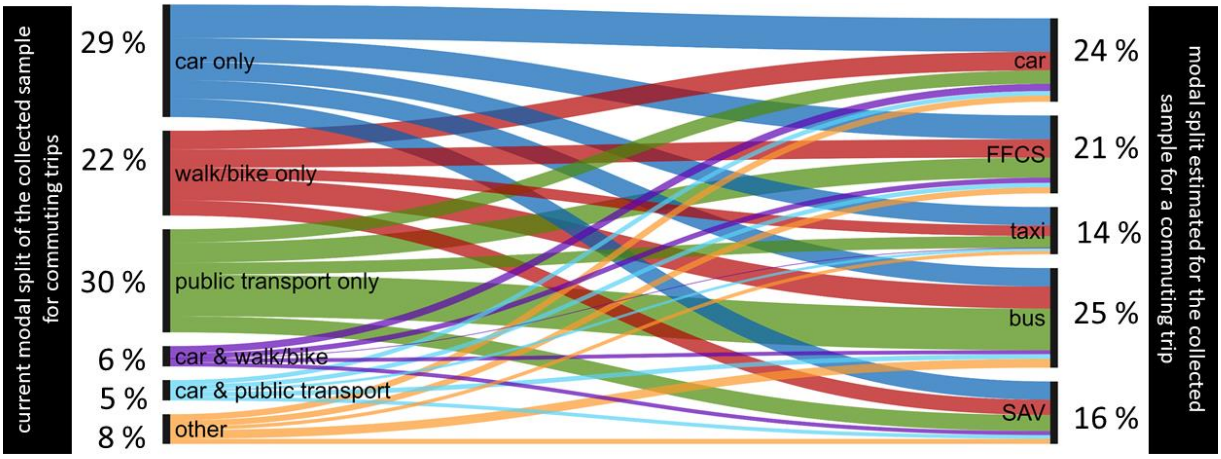


Figure 3.4: Estimated mode migration patterns: current (left) and estimated (right) market shares per commuting mode(s)

The model allows taking a closer look at the effect of vehicle sharing and vehicle automation, by directly comparing *car* with *FFCS* and *taxi* with *SAV* respectively. Those currently commuting by combining car and public transport have an estimated probability of 18% to choose *SAV*, which is a higher probability than in other commuter groups. Those currently commuting by public transport have the lowest probability of choosing *SAV* (14%). When comparing the choice probabilities of *SAV* and *taxi*, it can be seen that all commuter groups, except those using mainly the car, clearly favour *SAV* over *taxi*. The probability for choosing *FFCS* is for all commuters higher than for *SAV*, ranging from 18% for public transport users and 22% for those currently taking the car or combing car and walking/cycling. The latter group has an equal preference for *car* and *FFCS*. However, for all other groups is the preference for *FFCS* much stronger than the one for *car*, the strongest difference can be observed for those currently combing the car and public transport for commuting.

3.4 Discussion and Conclusion

Currently, on-demand transport services are labour-cost intensive and therefore provided mainly to the elderly, passengers with special needs or in rural areas. With the introduction of digitalized mobility forms and services, on-demand transport can be offered on a larger scale against limited costs, expanding the pool of potential users. In this paper, it is analysed how the introduction of free-floating car-sharing and shared automated vehicles on a large-scale could change mode preferences for different user groups.

3.4.1 Preferences for Shared (Automated) Modes

While stated choice experiments are an opportunity to capture preferences about novel alternatives, they bear the risk that uncertainty, expectations and current risk perception are influencing the choices made and respondents might develop a different attitude towards these modes once they become more familiar with them (Krueger et al., 2016b). Therefore, the outcome of this experiment can only be an indication of the current perception of the utility of the new modes, and not a forecast of mode preference once the presented modes might become broadly available. Bearing this in mind, the results of the analyses offer the following insights in terms of the perception of shared and shared automated vehicles:

- **Car commuters are open for using shared mobility services providing a similar experience to their current mode, but they are not charmed by vehicle automation**.
  The findings of the migration analysis suggest that commuters who currently mainly use a private car show a high preference for *FFCS*. The migration to *FFCS* from this group can be further amplified when charging parking fees (which are not included in the simulated scenario), considering that the class of *Car Captives* shows a strong aversion towards parking costs.
  Commuters taking the car show a lower preference for the other modes of shared mobility included in the choice experiment. This group perceives the utility of *SAV* marginally lower than the utility of *taxi*, indicating this group does not see vehicle automation to be an added value in itself. *Car Captives* have been found before to be less likely to switch to SAV (Haboucha et al., 2017).

- **Commuters currently combining car and public transport are the most enthusiastic about shared (automated) mobility services.**
  Commuters currently opting for a combination of car and public transport for their commute are the most enthusiastic about *FFCS* and *SAV*. This group shows the strongest preference towards these modes and also shows the strongest difference in the perceived utility between *car* and *FFCS*, and the second-strongest difference in the perceived utility between *taxi* and *SAV*. This indicates that the added value of the new shared (automated) mobility service is the strongest for this group. A possible reason for this could be that this group has mobility needs that are neither met by a car or public transport services alone, and that *FFCS* and *SAV* are perceived to close this gap by combining the advantages of a car and public transport services.

- **Public transport users are the least impressed with on-demand shared (automated) mobility services.**
  For commuters currently using public transport, the introduction of shared automated vehicles increases the perceived utility for on-demand door-to-door services, as for this group a higher probability for choosing *SAV* than for choosing *taxi* has been estimated. However, no other group has lower mode choice probabilities for *FFCS* and S*AV* than this group. The latent class analysis shows that *Public Transport Enthusiasts* have a higher probability to feature older respondents and respondents having a lower level of education, and captures those that are more cost-averse rather than time-loss-averse. This group of people has been found before to be less likely to opt for automated vehicles (Gkartzonikas & Gkritza, 2019).

- **Young and time-sensitive commuters are the most appreciative of vehicle automation.**
  The class of participants showing the greatest enthusiasm for *FFCS* and *SAV* are captured in the class of the *Brisk Sharers* (63% of the sample), who also show a strong preference for travelling in *SAV* over *taxi*. This class is characterised by being younger and more educated than the sample average.

- **Commuters currently cycling or walking see an added-value in vehicle automation.**
  The group of commuters currently walking or cycling to work shows the strongest difference in the perception of *SAV* and *taxi*. It should be noted that the mode choice experiment did not incorporate active mode options and thus forced this group to select exclusively between motorized modes. The estimated model therefore merely captures the difference in mode perceptions between the included modes, and not the perceived utility in relation to the modes this group is currently using.

The findings in this study largely corroborate the image of the “early adopters” of shared (automated) vehicles sketched in previous studies, as summarized in the introduction. The main difference is that in this study neither gender nor the number of children significantly improved the clustering of the observed choices. Instead, the current mode choice showed to be a more reliable predictor for the collected sample. Different from Krueger et al. (2016), the public transport users included in our study showed the lowest preference for SAV. In fact, survey respondents who combine public transport use and private car for their commuting trips showed the highest preference for SAV, as well as for FFCS. Indeed, our study showed that multi-modal commuters and those using active modes (walking or biking) have the highest preference for the new modes. Therefore we suggest adding these characteristics to the image of an “early adopter” of shared (automated) mobility services.

3.4.2 Policy Implications

The discussion around the description of the “early adopter” of new digitalized mobility forms and services does not include consequences for “late adopters”. From the results of this study, as well as the findings in similar studies, it can be deduced that such modes primarily meet the travel needs of a group that currently already has a high degree of flexibility in mode choices, while those currently dependent only on a private car or on public transport show the lowest preferences for the on-demand transport services included in the choice experiment. The potential added value of FFCS and SAV differs for these two distinct groups. Car users, even if they are captive users, typically already have a fast and comfortable mode at their disposal.

For this group, the study points to a clear trigger that could support the switch from using the private car to shared options: the “nuisance of parking”. Both the time having to spent on searching a parking spot and the costs of parking influenced the expressed mode preferences significantly. Ambitious urban parking management that makes room for shared mobility services and limits (free) parking possibilities for private cars has thus the potential to play an important role in making the shared services a success story, also among this user group. Research corroborates this, as a number of studies show that parking availability and costs are prime factors influencing the use of car-sharing systems (Ferrero et al., 2018) and parking search time impacts the willingness to use shared automated vehicles (Barbour et al., 2019).

The situation for the second group, consisting of public transport users, is quite different, however. These respondents showed the lowest preference for the new transport modes in our study. This may in part be because of a general satisfaction with the quality of public transport or it may be because of the costs related to new digitalized mobility forms. If the latter is the case, it implies that such new modes will do little to enhance the choice set for this user group or for enhancing the ease with which they can get around. This raises concerns, as it is especially the group of public transport dependents who are at risk of transport poverty. Policy interventions that reduce the costs of using FFCS and SAV may thus be necessary if these new mobility forms are to enhance the inclusiveness of the transport system.

3.4.3 Study Limitations and Outlook

The limitations of this study are primarily related to the inclusion of unknown alternatives in the choice experiment, potentially leading to a hypothetical bias in the context of estimating the willingness-to-pay. The estimated model therefore only offers a first step in quantitatively analysing current preferences towards FFCS and SAV, but does not represent a full mode choice model for an era where these modes might become widely available. The choice experiment has been complex in the compositions of the choice alternatives, so various important aspects could not be included in order to not burden the respondents with an overload of information and options. Future studies could extend the scope of this experiment in terms of additional mode alternatives, trip purpose, and trip distance. It would be particularly important to consider slow modes as part of the choice-set in order to see the difference in perception of the new shared (automated) modes and walking and cycling. Also the important factors waiting time and travel time reliability were not included in the choice experiment. These could, however, prove to be quite influential for the perceived utility of FFCS and SAV, since for these modes a new dimension is added in this respect, namely the uncertainty of vehicle availability. Finally, future work could address the issue of the dominant alternative specific constants by including additional factors explaining the preference towards FFCS and SAV, such as trust in the new technology or the concept of reliability in regard to on-demand transport services.

The results presented in this study allow examining how different user groups currently perceive free-floating car-sharing and shared automated vehicles for commuting purposes. It is likely that mode perception changes with the level of familiarity with it, therefore it will be necessary to continuously update mode choice preference of the different user groups towards new forms of shared mobility along with their introduction to the market. A series of attitudinal questionnaires accompanying gradually the introduction of the new vehicle technology and related new mobility services will allow future studies to monitor how the perceived utility of the new modes evolves over time with the increasing availability of large-scale free-floating car-sharing systems and shared automated vehicles.

Part II – Fleet Operation

For a long time, the transport market recognized three major categories of transport modes: (1) active modes such as walking or cycling, (2) public transport modes such as buses or trains and (3) private motorized modes such as cars or motorcycles. Lately, new forms of transport technologies and transport services have been emerging which blur the lines between these three categories. Enabled by striking developments in communication technologies, these new modes and transport services aim at providing faster and more convenient transport tailored to the individual needs and preferences of their customers. Examples are all forms of so-called “shared mobility” – comprising electric kick-scooters, bikes, cars, motor scooters and ride-hailing services – as well as smart cards used in public transport services, real-time travel information services or mobility-as-a-service (MaaS) concepts. All these new mobility options cater to users who value flexibility. The selling point of such flexibility-oriented services is, that by switching from “owning” to “using”, one does not have to worry about the responsibilities that come with possession – such as investment costs, insurances, maintenance – while getting the same, or even better, transport services than those privately owning such means of transport.

Operating mobility services that do not require private vehicles is traditionally the domain of public transport authorities. However, when it comes to providing services that adapt flexibly to the transport needs of the users, public transport authorities have little experience. Planning paradigms for flexible mobility services are therefore often developed from the point of view of private operators, focusing mainly on service efficiency and profit maximization. In this thesis, a future is envisioned in which also public transport authorities have flexible mobility services in their portfolios, made financially feasible by employing self-driving vehicles. The analysis of service performance, therefore, includes next to the efficiency of the service operation also the service provision equity and service externalities. In the following chapters, we simulate the operation of a centrally dispatched fleet of shared automated vehicles. In particular, we focus on the operational decision of where to place idle vehicles during the day. Various relocation strategies are tested for a small case study without constrained parking facilities (Chapter 4) and a larger case study, based on the city of Amsterdam, in which dedicated parking facilities are limited (Chapter 5).

Chapter 4 - Impact of Relocation Strategies for a Fleet of Shared Automated Vehicles on Service Efficiency, Effectiveness and Externalities

This chapter is based on: Winter, K., Cats, O., Martens, K., van Arem, B. (2017). Impact of Relocation Strategies For a Fleet Of Shared Automated Vehicles On Service Efficiency, Effectiveness and Externalities. 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems, MT-ITS 2017 - Proceedings

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 the largest reduction of the number of parked vehicles per link, and the strategy of anticipating demand to the largest reduction of deadheading mileages.

4.1 Introduction

With the technology of vehicle automation progressing fast, the question arises on 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 (Azevedo et al., 2016; Cyganski, 2016; Fagnant & Kockelman, 2014). 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 modelling 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 (Maciejewski, Bischoff, & Nagel, 2016). When simulating the operation of SAV, a main focus lies on the dispatching process and the fleet size determination (Maciejewski et al., 2016; R. Zhang, Rossi, & Pavone, 2016).

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 (Wong, Szeto, & Wong, 2014). The latter is unfavourable from a societal perspective due to its negative external effects of inducing additional traffic (Cai et al., 2016), 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 (R. Zhang et al., 2016). This advantage allows developing 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 (Fagnant & Kockelman, 2014; Maciejewski et al., 2016), move to meet excepted future demand (R. Zhang et al., 2016) or move to balance vehicle supply in the network (Azevedo et al., 2016; Fagnant & Kockelman, 2014; R. Zhang et al., 2016). 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 centre.

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

4.2 Methodology

4.2.1 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 remain 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 fulfils this profile, the vehicle moves to a random one out of these zones. The centre 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.

4.2.2 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 (Nagel, Kickhoefer, Horni, & Charypar, 2016), 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 vehicle 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, the maximum number of idle vehicles per link (link occupancy), and the total duration of vehicles remaining idle on a link during peak hours.

4.2.3 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 (Maciejewski, 2016). Vehicles and travellers are modelled as dynamic agents: vehicles perform tasks according to their individual schedules, which is constantly updated by the dispatcher, while travellers 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 (Nagel et al., 2016). 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* (Maciejewski et al., 2016), 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 behavioural model underpinning passengers travel choices (Maciejewski et al., 2016).

4.2.4 Case Study

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.

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 (Maciejewski et al., 2016). The pick-up time per customer 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 deviation 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 4.1). This allows observing 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 centre of the network (Figure 4.2). 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 4.2, are twice as likely to be a home or work location as the links in the right side.

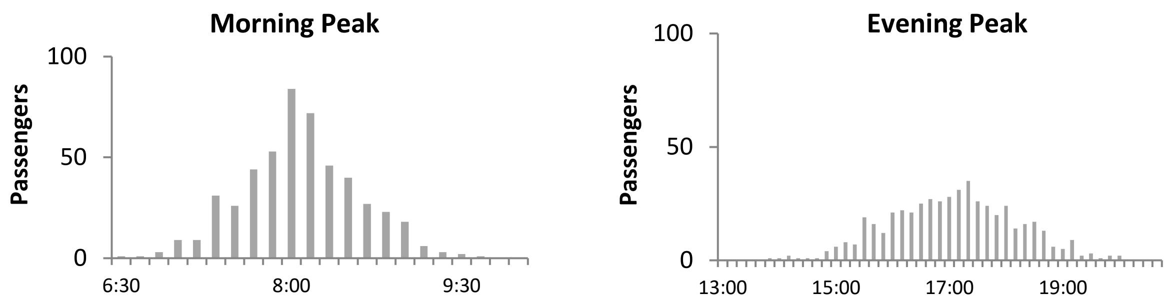


Figure 4.1: Simulated Demand in the morning peak (left) and evening peak (right)

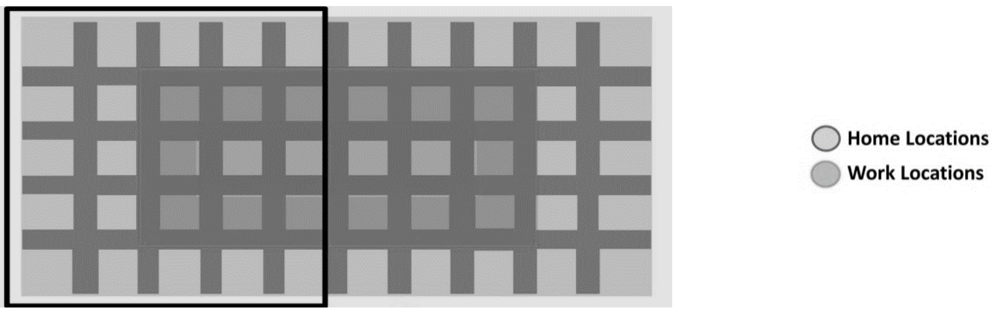


Figure 4.2: Spatial situation of the home locations (light gray) and the work locations (dark grey) in the grid network. In the case of off-centered demand, the likelihood of a link being home/work location is twice as high in the black rectangle

Simulation Settings

Travelling agents in MATSim select the plan for the next simulated day based on the performance of previous plans (Nagel et al., 2016). The memory of each agent is set to maximum 5 iterations, or simulated days. In 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 4.1, based on m initial simulation runs, with the one leading to the largest number of runs being the decisive one:

$$N(m) = \frac{SD(m) * t_{m-1,\frac{1-\alpha}{2}}}{\bar{X}(m) * \epsilon} \tag{4.1}$$

where $\overline{X}(m)$ 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, ϵ = 0.1 and α = *0.1*, this results in 3 to 7 simulation runs per scenario.

4.3 Results

The outcome for the KPIs under the different relocation strategies is presented in average values (Table 4.1) and is discussed in more detail in the following.

Table 4.1: Average results of the relocation strategies

Centred Demand	***Remaining Idle***	***Random Shuffle***	***Rebounding***	***Demand Anticipation***	***Even Dispersal***
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-Centred Demand	***Remaining Idle***	***Random Shuffle***	***Rebounding***	***Demand Anticipation***	***Even Dispersal***
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

4.3.1 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 were 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 4.1). The average travel time per passenger for the centred demand is 13.52 minutes, for the off-centred demand 13.43 minutes. This includes 2 minutes pick-up time and 1 minute drop-off time.

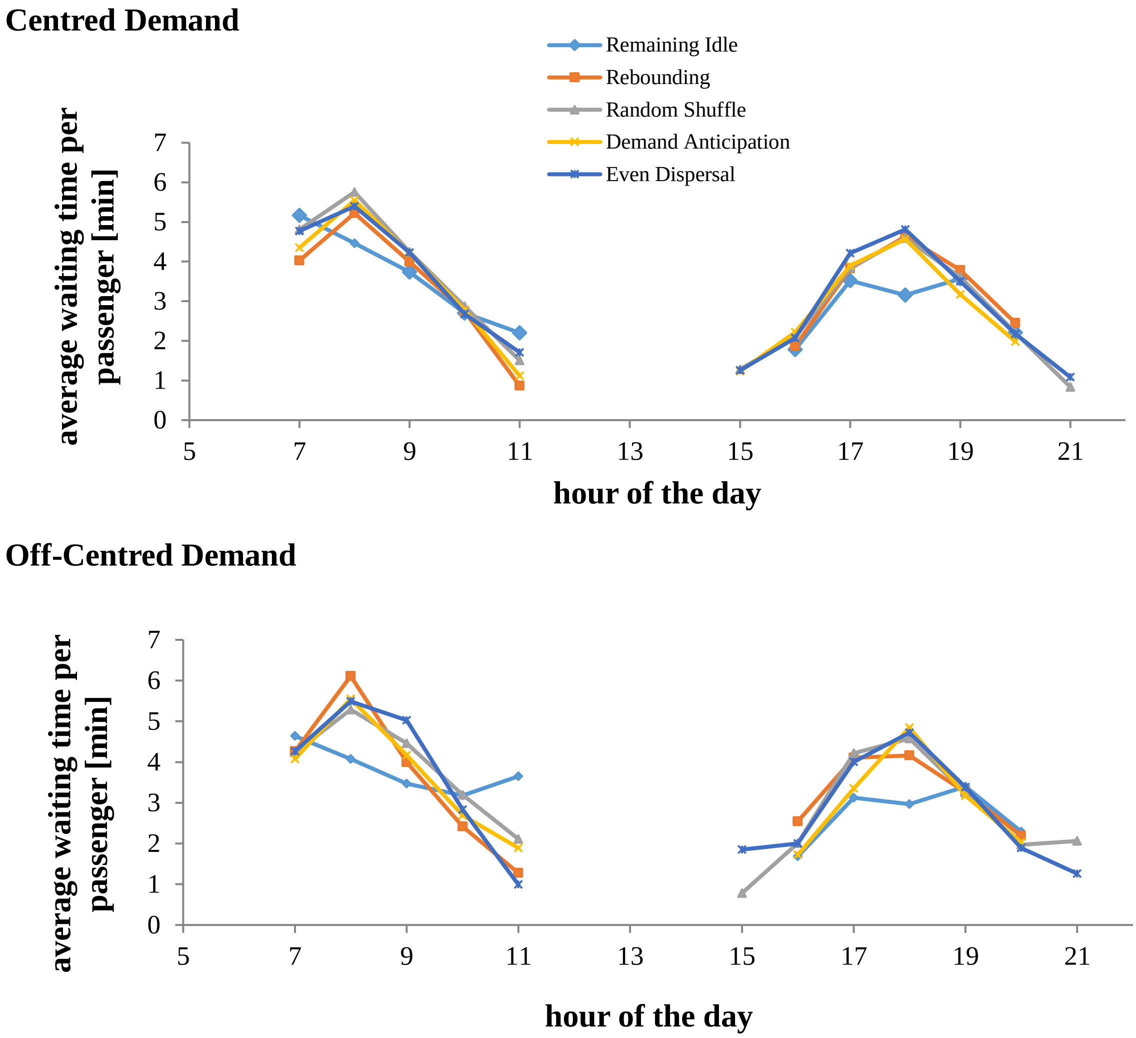


Figure 4.3: Average waiting times per hour per passenger for the centered demand (top) and the off-centered demand (bottom)

The tested relocation strategies have a great impact on service efficiency, as can be seen in the differences in average waiting time (Table 4.1). These differences are especially large for the off-centred 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 favourable 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 centred demand and Demand Anticipation also in the case of off-centred 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 centred demand (Table 4.1), 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-centred demand (Table 4.1). This is again a result of the nature of the demand favouring 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 over the network in case of off-centred demand (Figure 4.3, bottom).

As can be seen in Figure 4.3, 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 4.3, 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.

4.3.2 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 kilometres 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 4.1). This leads to a decrease of overall vehicle use time by 5% (about 3 percentage points) compared to the strategies relocating vehicles.

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 centred and off-centred demand (Table 4.1). This is the result of spreading the vehicles spatially as much as possible. As can be seen in Figure 4.4, 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.

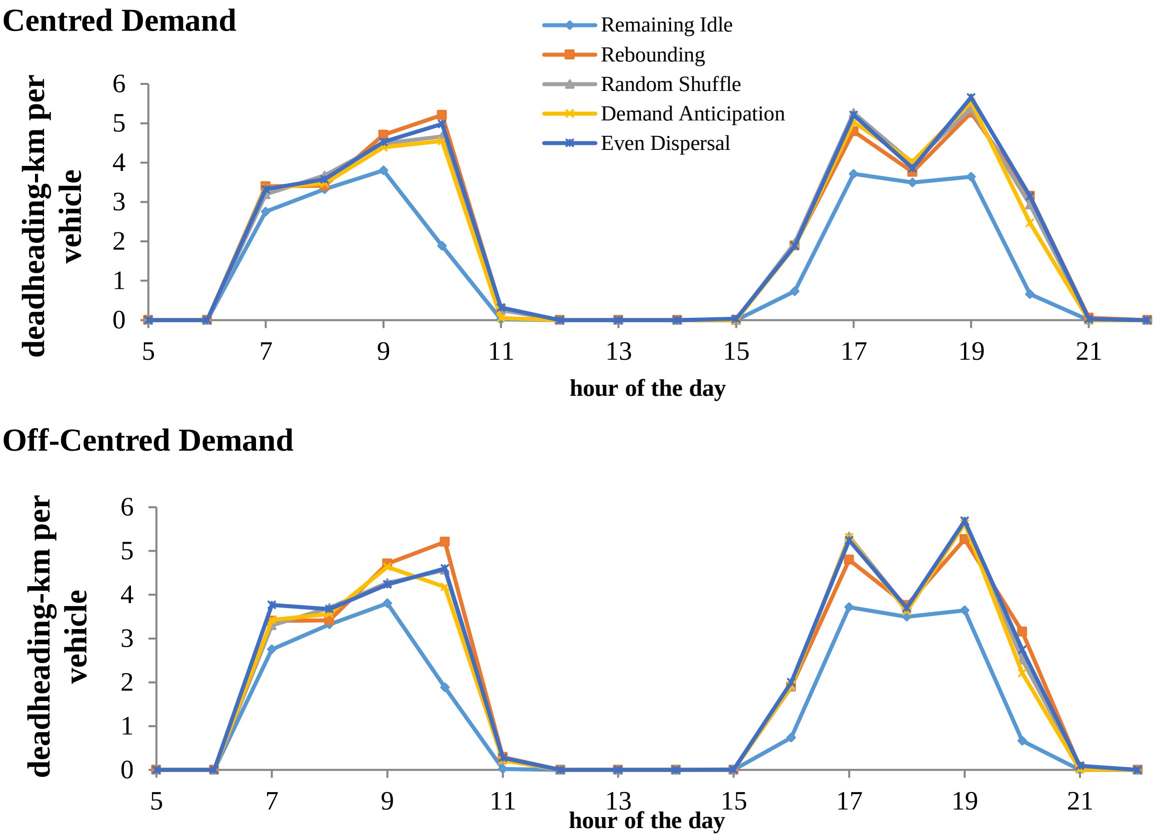


Figure 4.4: Average deadheading-km per hour per vehicle for the centered demand (top) and the off-centered demand (bottom)

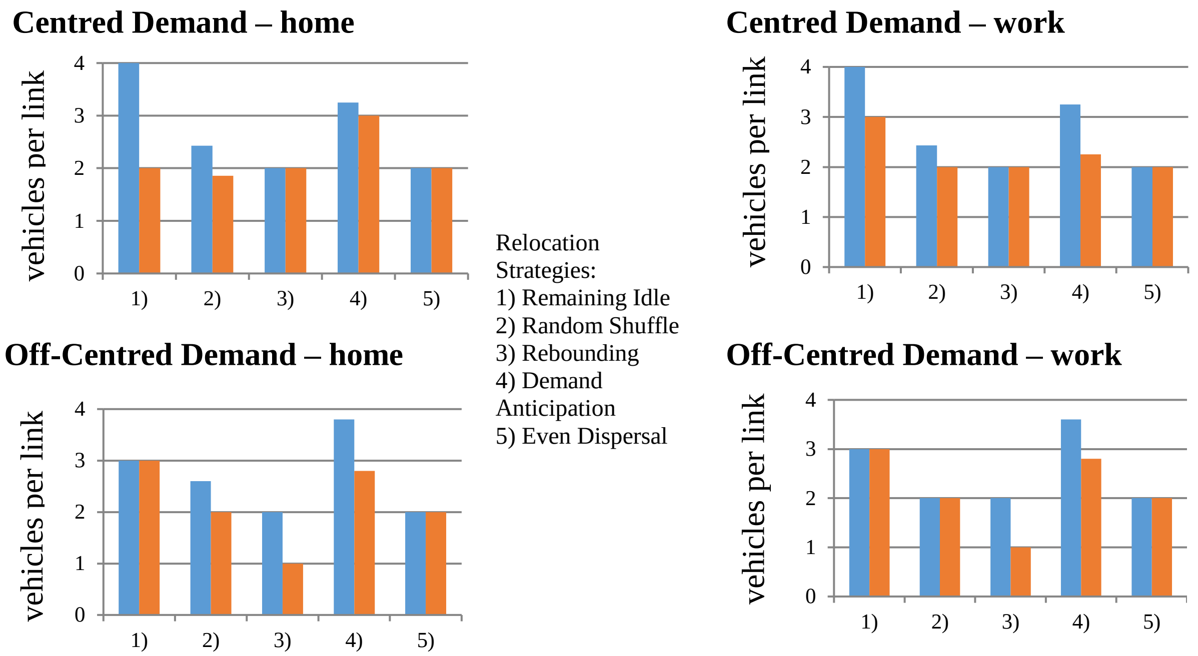


Figure 4.5: Daily maximum number (blue) and second highest number (red) of idle vehicles per link in the home area (left) and the work area (right) for the centered demand (top) and off-centered demand (bottom)

4.3.3 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 analysed 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 (Pierce & Shoup, 2013). Therefore, a relocation strategy is considered favourable when leading to as little idle vehicles per link as possible.

As can be seen in Figure 4.5, in case of the centred 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 the case of off-centred demand, this effect is even stronger, which makes *Demand Anticipation* the least favourable 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 favourable 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 (Pierce & Shoup, 2013). The comparison of the average duration of idle stays during peak-hours, as indicated in Table 4.1, shows that *Remaining Idle* leads to the longest idle times for the centred 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.

As shown in Figure 4.6, 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 centred and off-centred 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 fewer 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 favourable strategies in terms of parking turnover rates.

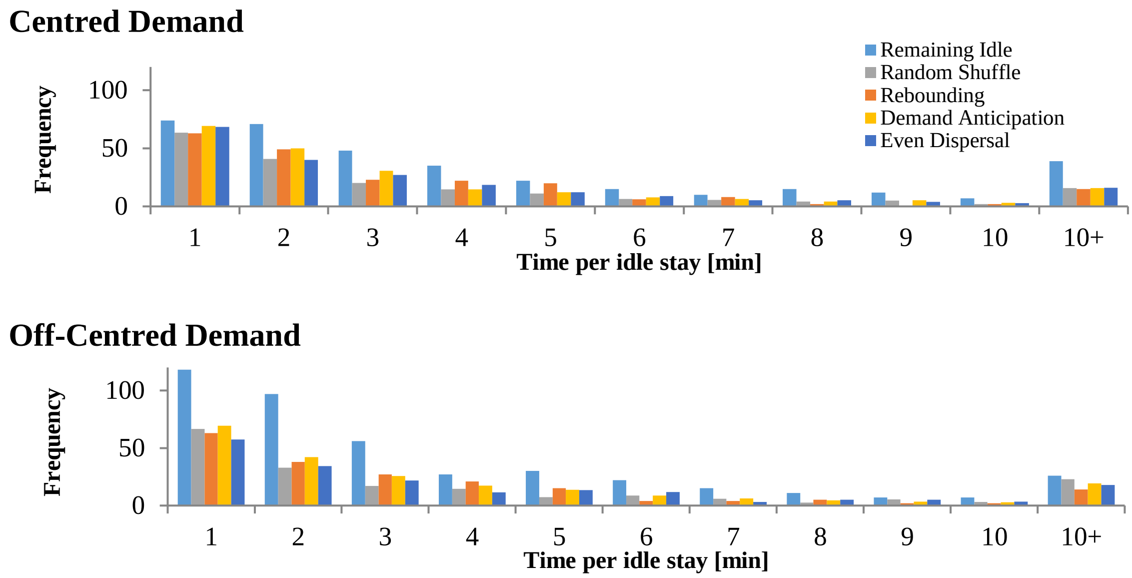


Figure 4.6: Frequency of idle stays per idle time in minutes for the centered demand (top) and the off-centered demand (bottom)

4.4 Discussion and Conclusion

The simulation of the operation of SAV with five different relocation strategies for idle vehicles in a simple case study allows quantifying 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 centre 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 analyse 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 analysed 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 analysed in more depth in order to ensure a successful introduction of the new demand-responsive urban mobility services.

Chapter 5 - Relocating Shared Automated Vehicles Under Parking Constraints: Assessing the Impact of Different Strategies for On-Street Parking

This chapter is a revised version of: Winter, K., Cats, O., Martens, K., van Arem, B. Relocating Shared Automated Vehicles Under Parking Constraints: Assessing the Impact of Different Strategies for On-Street Parking. Under Review.

Abstract

With shared mobility services becoming increasingly popular and vehicle automation technology advancing fast, there is an increasing interest in analysing the impacts of large-scale deployment of shared automated vehicles. In this study, a large fleet of shared automated vehicles providing individual rides to passengers is introduced to an agent-based simulation model based on the city of Amsterdam, the Netherlands. The fleet is dimensioned for a sufficient service efficiency during peak-hours, meaning that in off-peak hours a substantial share of vehicles is idle, requiring vehicle relocation strategies. This study assesses the performance of alternative relocation strategies for on-demand passenger transport under constrained curbside parking capacity. Three zonal pro-active relocation heuristics are tested: (1) demand-anticipation, (2) even supply dispersion and (3) balancing between demand and supply of vehicles. The strategies are analysed in regard to service efficiency (passenger waiting times, operational efficiency), service externalities (driven mileage, parking usage) and service equity (spatial distribution of externalities and service provision). The demand-anticipation heuristic leads to the highest average waiting times because vehicles bunch around hotspots of demand. This results in an uneven usage of parking facilities, resulting in local shortages of parking spaces. The most favourable results in regard to service efficiency and equity are achieved with the heuristics balancing demand and supply, at the costs of higher driven mileage due to the relocation of idle vehicles. These results open up opportunities for municipalities to accompany the introduction of large fleets of shared automated vehicles with suitable curbside management strategies that mitigate undesired effects.

5.1 Introduction

The development of technology for automatically driven vehicles is progressing fast. This raises not only questions about the impact of fully automated vehicles (AV) on future mobility and traffic patterns, but also on their impact on the existing infrastructure. High degrees of vehicle automation allow the introduction of vehicles that drive autonomously, which can thus be shuffled from one place to another without having a human on-board. This opens up new opportunities in the field of car-sharing, in which currently one of the main challenges is to balance the supply of car-sharing vehicles with the demand for them. In this paper, we analyse the performance of a large fleet of shared automated vehicles (SAV). Such cooperative fleets bring new challenges to the operators and regulators of such mobility services, as they neither follow fixed schedules nor fixed routes. One of these challenges is the question, how to deal with idle vehicles whose services are currently not required. This is especially a pressing issue in off-peak hours, when larger number of idle vehicles need to be managed. The focus of this study is put, in particular, on strategies for relocating idle SAV, and how these influence the performance of the transport service offered by SAV, as well as the consumption of parking space and the overall mileage driven by the SAV. The constraints caused by the scarcity of parking space is an issue often overlooked in past studies simulating the operation of SAV or similar on-demand transport services with unlimited parking facilities, despite the substantial impact such constraints have on the performance of such a service.

The SAV transport service in this paper is envisioned as an on-demand transport service operated by a fleet of automated vehicles that require no human intervention (level 5 automation; or level 4 automation if only operated on a selection of suitable roads). In countries with high labour cost, on-demand systems are currently either highly subsidized (and often limited to users with special needs or those living in remote areas) or expensive (and primarily used by strong socio-economic groups), with operating costs often more than three times higher than for schedule-based transit services (J. M. Anderson et al., 2014; Wright, Emele, Fukumoto, Velaga, & Nelson, 2014). By deploying AV, flexible door-to-door services could be implemented on a larger scale at much lower costs, which could become an important enrichment of the current schedule-bound public transit services. Another advantage of SAV is, that - differing to on-demand transport services operated by human drivers (e.g. ride-sourcing) - vehicles can be programmed to fully comply with the central dispatcher’s orders and can relocate themselves accordingly (R. Zhang et al., 2016), and that vehicles belonging to the same fleet are not competing against each other for revenue. The results of the model analysis in this study would also hold for any non-automated on-demand transport service strictly following the advice of the central dispatcher.

For an on-demand system operated by SAV to have sufficient spatial coverage and level-of-service, large fleets of AV have to be employed, as various simulation studies have shown (Alonso-mora, Samaranayake, Wallar, Frazzoli, & Rus, 2017; Bischoff & Maciejewski, 2016; T. D. Chen, Kockelman, & Hanna, 2016; International Transport Forum, 2015). In these studies, thousands of shared AVs have been introduced to serve demand in large cities. Their search for the appropriate fleet sizes is mainly driven by targets concerning the level of service, most commonly expressed in passengers’ waiting times and/or trip times, either as an average or in terms of a minimum level of service. By setting these kinds of boundary conditions, fleet sizes are dimensioned to cater for the maximum demand occurring during peak hours. Consequently, there will be idle vehicles during off-peak hours, which can either be “stored” on the road network by letting the vehicles cruise empty or park on on-street parking facilities, or be sent to off-street parking facilities (depots). The problem of the relocation of idle vehicles in the operation of large fleets of vehicles is one of the central challenges and a potential barrier for the introduction of large-scale shared on-demand transport services, be it for conventional taxi services or services operated by SAV (Babicheva, Burghout, Andreasson, & Fail, 2018; Dandl & Bogenberger, 2019; Sayarshad & Chow, 2017; Winter, Cats, van Arem, & Martens, 2017).

In this paper, idle vehicle relocation is not regarded solely as a supporting step to an efficient vehicle dispatching, but also as a means to manage idle vehicles not in use according to principles reflecting all stakeholders' interests. With this vision on vehicle relocation, we move from the question on where to simply "store" idle vehicles on to the question, how vehicle relocation can effectively improve the service operation of a fleet of vehicles while mitigating undesired external effects caused by the service. In particular, the performance of three heuristics for the proactive relocation strategies *Demand Anticipation*, *Supply Anticipation* and *Demand-Supply Balancing* is tested. These relocation strategies are compared in three aspects for selected key-performance indicators: (1) performance of the SAV system, (2) external effects and (3) service equity provided by the SAV system. The relocation strategies are simulated for this analysis in an agent-based simulation model of a large-scale case study based on the city of Amsterdam, the Netherlands. The main contributions of this study can be summarized by the following:

- Comparison of three pro-active relocation heuristics for shared automated vehicles under parking constraints.
- Introducing a fleet of shared automated vehicles into an agent-based model for a large-scale case study based on the city of Amsterdam.
- Holistic impact analysis of SAV in regard to service efficiency, service provision equity, and service externalities.

The remaining of this paper is structured as follows: In section 5.2, the problem of vehicle relocation for shared automated vehicles is described in more detail and approaches to this problem as described in the literature are discussed, and the three relocation strategies tested in this study are defined. In section 5.3, the modelling environment, the description of the network, the demand and the supply for SAV are described. In section 5.4, the simulation results are presented and analysed according to the impact criteria stated above. The paper is concluded with section 5.5, which provides a discussion of the results and an outlook on future research.

5.2 Relocating Shared Automated Vehicles

5.2.1 Problem Description

In Figure 5.1, a schematic overview is given of the chain of operations necessary for the deployment of SAV: vehicle dispatching, vehicle routing, and vehicle relocating. Vehicle routing and vehicle dispatching are integral steps of the operation of SAV. Vehicle relocation, however, is an optional step, as it can be alternatively decided to only move the vehicle from its latest passenger drop-off location to the next passenger pick-up location once the vehicle has been dispatched to a new request (which can occur instantly in case there is a queue of unserved requests). However, adding the additional step of relocating the vehicle to a strategically chosen parking location can potentially improve the overall performance and level-of-service. Furthermore, it would also be essential for operating real-world SAV systems due to limited parking facilities in urban environments. This is especially true in times where there is little demand for the service, e.g. during off-peak hours, which results in an oversupply of vehicles.

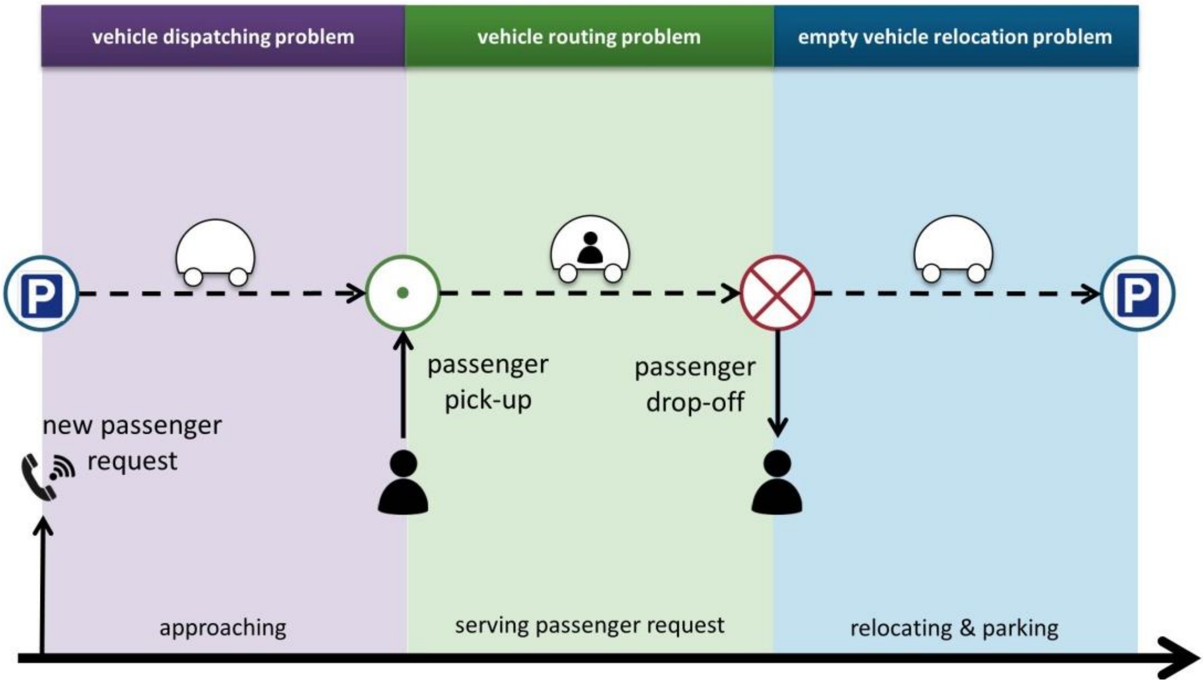


Figure 5.1: Chain of problems for operating an on-demand transport service: dispatching, routing and relocating

The relocation of idle vehicles has been described by the *Empty Vehicle Redistribution Problem*, which falls in the category of *Vehicle Routing Problems*, a subcategory of the *Travelling Salesman Problem* (Babicheva et al., 2018). Idle vehicle relocation has also been described as the *Idle Vehicle Propositioning Problem*, as a subcategory of *Facility Location Problems* (Sayarshad & Chow, 2017). These problems are NP-hard and are notoriously difficult to solve, especially in dynamic settings. For this reason, applying heuristics for the dispatching and relocation of vehicles in large cooperative fleets is the most common approach in simulation studies of large-scale on-demand transport systems.

5.2.2 Network

A directed graph $G(V, E)$ is used for representing the dynamic transport service network with E being a set of arcs (edges) and V being a set of vertices. Each vertex v represents an intersection between arcs and each arc e is described by its characteristics: link length, the maximum allowed driving speed, free flow capacity and the maximum parking capacity denoted by κ_e^{max}. At a discrete moment in time τ, the time-dependent variables of current driving speed and the current free parking capacity $c_e(\tau)$ describe the state of the arc. Furthermore, Z denotes a set of zones, described by the set of arcs present in that zone E_z and the time-dependent variables of the current free parking capacity of all arcs in zone z, $c_z(\tau) = \sum_{e \in E_z} c_e(\tau)$.

5.2.3 Demand for SAV

The demand for SAV has been modelled based on the general population dynamics implemented in MATSim (see Nagel et al. 2016). In MATSim, travellers follow a daily plan, which consists of a set of activities that they want to perform. For each activity, the location is known, as well as the desired start and end times and the mode the agents intend to use to reach the activity. Each traveller memorizes a set of these plans, for which the plans can vary in activity start and end times, modal choices or route choices, but always show the same sequence of activities. In the course of a repeated simulation of the same day, agents can try out different plans and improve parts of the plans according to predefined behavioural strategies also known as 'innovation rules'. The plan selection is based on the concept of utility maximisation, as performing an activity and travelling towards an activity are scored based on their perceived utility. The repeated plan innovation and plan selection in the face of the resulting traffic states leads to an optimization of the agents' plans through the co-evolutionary search for the resulting equilibrium (Balmer & Rieser, 2009), which is de facto also leading to a user equilibrium on the road network.

The demand for SAV is expressed in the form of individual requests. Each individual request $q \in Q$ is launched by an agent at time step τ at a pick-up (origin) location on an arc e_q^o, where Q is the set of all travel requests for SAV rides in the network under consideration. Information concerning the downstream drop-off location of a request is not used during the vehicle dispatching and relocating process. All requests that are not yet dispatched or are in the process of being dispatched are stored in the time-dependent set of open requests $Q(\tau)$.

5.2.4 Supply of SAV

Each SAV follows, similarly to the travellers, a schedule for the whole day, which is imposed on it by a central dispatcher. In contrast to the travellers, who update their plans from day to day, the vehicles' schedules are updated within each simulated day in response to passengers' requests.

The SAV are stored in a set of vehicles K. Each vehicle $k \in K$ is described by its length, the maximum vehicle speed, its current location denoted by $e_k(\tau)$ and its current dispatching status. Vehicles are grouped in subsets according to their dispatching status: the subset $K^{serve}(\tau)$, in which all vehicles currently assigned to dispatch a request (and are therefore moving – either empty towards a pick-up point or with a passenger on-board heading towards the drop-off location) are stored, and the subset $K^{idle}(\tau)$, in which all idle vehicles currently not assigned to dispatch a request are stored. The latter has a subdivision, the set of vehicles that are not in use and relocating according to one of the relocating strategies $K^{reloc}(\tau)$ and the vehicles that are idle and parked $K^{park}(\tau)$. Relocating vehicles are, despite being on the move, considered to be idle and can at any moment be diverted from their relocation path in order to serve an incoming request. It holds that $K^{serve}(\tau) \cup K^{idle}(\tau) = K$ and that $K^{reloc}(\tau) \cup K^{park}(\tau) = K^{idle}(\tau)$ since these sets are mutually exclusive and collectively exhaustive.

5.2.5 Vehicle Relocation Heuristics

In regard to the transport service provided by the SAV envisioned in this study, many parallels can be drawn between SAV and the current taxis, which also provide on-demand transport services. For this reason, we include in the review of relocation strategies for SAV also the strategies applied to taxis today. There are multiple heuristic vehicle relocation strategies for vehicles of on-demand services, which can be divided into two groups: reactive and proactive relocation strategies (Babicheva et al., 2018). Reactive relocation means that vehicles relocate only upon passenger request, while proactive relocation strategies relocate vehicles in anticipation of future demand and/or supply states. In the latter case, the step of relocating and dispatching are interconnected. The different strategies differ also in regard to their overall goal:

while some aim at increasing the chance for an individual vehicle to be dispatched to requests as often as possible, others are designed to improve the overall service of a fleet, to reduce undesired externalities or to support scheduled public transport services in regions with underdeveloped coverage, e.g. when used as last-mile service.

Two reactive relocations strategies can be distinguished: parking and cruising. Reactive strategies applying "parking" either park idle vehicles at their last drop-off location, which in the following we refer to as the strategy *Remain*, or send them to a taxi stand or depot. Though the reactive relocation strategy of parking at the last drop-off location is not commonly observed in the operation of demand-responsive transport services, it is often selected as a default option in simulation studies featuring SAV or similar on-demand transport services (Bailey & Clark, 1992; Ben-Dor, Ben-Elia, & Benenson, 2019; Bierlaire, 2006; Fagnant & Kockelman, 2014; Maciejewski et al., 2016; Winter, Cats, van Arem, et al., 2017), implicating that idle vehicles park at the last drop-off location regardless of parking (capacity) constraints. The relocation strategy of *Cruising* is a phenomenon that can be observed in the real world when drivers of on-demand transport services are searching for potential customers while avoiding parking search and possible parking fees, as is the case for regular taxis, ride-hailing services and many para-transit services in the Global South (D. N. Anderson, 2014). Idle cruising increases the driven vehicle mileage and, by this, can contribute to congestion effects, increased fuel consumption or energy usage and increased emissions. This strategy has been included in simulation studies (R. Zhang et al., 2016), mainly as a means for benchmarking proposed proactive relocation strategies in regard to driven mileage and service efficiency.

In this study, vehicles are assigned to incoming requests according to the "rule-based" dispatching strategy described in (Maciejewski & Bischoff, 2015; Maciejewski et al., 2016). In times of oversupply of vehicles, this dispatching strategy assigns the nearest vehicle to customer requests in a first-in-first-out (FIFO) order of the requests, and in times of undersupply of vehicles assigns the next idle vehicle to the closest open customer request. In case no open requests remain to be dispatched, the vehicles stay idle at the drop-off location of the last request they have been serving, the relocation strategy applied by default in the "rule-based" dispatching strategy is thus *Remain.* The *Remain* strategy does not take into account that in the real world, parking space and road space are limited resources. Letting vehicles simply wait at their latest drop-off location is hence an unrealistic representation of the operation of SAV or other comparable mobility services. We therefore consider three more advanced relocation strategies taking parking constraints into account, which we referred to as (1) *Demand Anticipation*, (2) *Supply Anticipation* and (3) *Demand-Supply Balancing*[2]. A detailed description of these strategies as used in this study and as found in the literature is provided in the following sections. The three strategies used in this study are composed of simple heuristic building blocks (described in pseudo-code in Figure 5.2), making them comparable and traceable. The first strategy aims at placing idle vehicle close to future demand, the second strategy aims at distributing idle vehicles throughout the network and the third strategy aims at meeting both goals of the previous strategies by mitigating future demand-supply deficits. All strategies are put into action on a zonal level.

The relocation of an idle vehicle k is performed in all cases when there is no pending unassigned request and the vehicle in question has been serving a passenger request in the previous time step and is currently idle. The relocation strategy determines the vehicle destination link so that

[2] Not all relocation strategies that were simulated, are presented in this chapter. In the Appendix, a complete overview over all simulated relocation strategies with a brief description is presented.

it moves from its current location $e_k(\tau)$ to the selected destination arc e_k^d. The three pro-active relocation strategies analysed in this paper are based on predictions of future demand and supply per zone, for which a rolling horizon time αh is defined, where α is a parameter that sets the number of horizon windows considered, each of which is h minutes long. For reasons of simplicity, we make usage of our full knowledge about future requests, the expected future demand is thus the true demand based on the agents' plans, and not an estimation thereof. The results for this strategy, therefore, are an overestimation of the performance of this relocation strategy, which in reality will be subject to prediction errors.

if $k \in K^{idle}(\tau) \wedge k \in K^{serve}(\tau - 1) \wedge \mathrm{Q}(\tau) = \emptyset$,

// for the search of potential zones of destination, only include those with free parking available
$\mathrm{Z_p} = \{\mathrm{z} \in \mathrm{Z} \,|\, \mathrm{c_z}(\tau) > 0\}$

Case "Demand Anticipation":
// determine set of potential zones of destination
if $\max\limits_{\mathrm{z}\in\mathrm{Z}} |\mathrm{Q_z}[\tau, \tau_h + \alpha h]| > 0$
for i = 1 to ζ
$\mathrm{z_i} = \underset{\mathrm{z}\in\mathrm{Z_p}}{\mathrm{argmax}}(|\mathrm{Q_z}[\tau, \tau_h + \alpha h]|)$
$\mathrm{Z'} \cup \{\mathrm{z_i}\}$
$\mathrm{Z_p} := \mathrm{Z_p} \backslash \mathrm{Z_i}$
$\mathrm{z}^* = \underset{\mathrm{z}\in\mathrm{Z'}}{\mathrm{argmin}}(\mathrm{d}(\mathrm{e_k}(\tau), \mathrm{e_z}))$
Otherwise
// determine closest zone with free parking available
$\mathrm{z}^* = \underset{\mathrm{z}\in\mathrm{Z_p}}{\mathrm{argmin}}(\mathrm{d}(\mathrm{e_k}(\tau), \mathrm{e_z}))$

Case "Supply Anticipation":
if $\max\limits_{\mathrm{z}\in\mathrm{Z}} \left|K_z^{park}[\tau, \tau_h + \alpha h]\right| > 0$
for i = 1 to ζ
$\mathrm{Z'} \cup \{\mathrm{z_i}\}$
$\mathrm{Z_p} := \mathrm{Z_p} \backslash \mathrm{Z_i}$
$\mathrm{z}^* = \underset{\mathrm{z}\in\mathrm{Z'}}{\mathrm{argmin}}(\mathrm{d}(\mathrm{e_k}(\tau), \mathrm{e_z}))$
Otherwise
// determine closest zone with free parking available
$\mathrm{z}^* = \underset{\mathrm{z}\in\mathrm{Z_p}}{\mathrm{argmin}}(\mathrm{d}(\mathrm{e_k}(\tau), \mathrm{e_z}))$

Case "Demand-Supply Balancing":
if $\max\limits_{z\in Z}\left(|Q_z[\tau, \tau_h + \alpha h]| - \left|K_z^{park}[\tau, \tau_h + \alpha h]\right|\right) > 0$
for i = 1 to ζ
$\mathrm{z_i} = \underset{\mathrm{z}\in\mathrm{Z_p}}{\mathrm{argmax}}(|Q_z[\tau, \tau_h + \alpha h]| - \left|K_z^{park}[\tau, \tau_h + \alpha h]\right|)$
$\mathrm{Z'} \cup \{\mathrm{z_i}\}$
$\mathrm{Z_p} := \mathrm{Z_p} \backslash \mathrm{Z_i}$
$\mathrm{z}^* = \underset{\mathrm{z}\in\mathrm{Z'}}{\mathrm{argmin}}(\mathrm{d}(\mathrm{e_k}(\tau), \mathrm{e_z}))$
Otherwise
// determine closest zone with free parking available
$\mathrm{z}^* = \underset{\mathrm{z}\in\mathrm{Z_p}}{\mathrm{argmin}}(\mathrm{d}(\mathrm{e_k}(\tau), \mathrm{e_z}))$

// determine arc on which relocating vehicle will park
$\tilde{\mathrm{e}}_\mathrm{k} = \underset{\mathrm{e}\in\mathrm{E_{z^*}}}{\mathrm{argmax}}(|\mathrm{c_e}(\tau_h + \alpha h)|)$

Figure 5.2: Pseudo-code for the relocation strategies simulated in this study

Relocation Strategy "Demand Anticipation"

Demand-anticipatory strategies relocate vehicles to places where high demand for their services is expected in the near future. They can be observed in the real world where on-demand services are not strictly regulated and drivers have to compete for customers. As drivers typically lack information on (future) demand, this can lead to many vehicles heading to the same high demand locations, causing an imbalance in the supply of vehicles, which can lead to overall lower system performance, lower service availability in some areas, undesired bunching of vehicles in the network and an increase in driven mileage (D. N. Anderson, 2014; Cetin & Deakin, 2019; Sayarshad & Chow, 2017; Zheng, Rasouli, & Timmermans, 2018).The simulation of demand anticipatory strategies are either based on the assumption of full knowledge of the future demand (Hörl, Ruch, Becker, Frazzoli, & Axhausen, 2019; Winter, Cats, van Arem, et al., 2017; R. Zhang et al., 2016), or at least of the expected arrival rates (Sayarshad & Chow, 2017; R. Zhang et al., 2016), or aim at modelling the risk-taking preferences of the operator (van Engelen, Cats, Post, & Aardal, 2018). The quality of the forecast of demand for SAV depends on the aggregation level of the spatio-temporal demand forecast. A framework for tackling this problem is presented in Dandl et al. (2019), showing that using more aggregated zoning (edge length of 2.5 km) reduces empty mileage and hence improves the service provided by SAV.

For the strategy *Demand Anticipation*, as formulated in this study, expected future requests are determined per zone for the time span between τ and $\tau + \alpha h$, and are stored in the temporary set of cumulative open requests $Q[\tau, \tau + \alpha h]$. From the set of ζ zones with the largest amount of open request, the zone $z*$ closest to the current position of the vehicle $e_k(\tau)$ is chosen, under the condition that at there is currently at least one free parking spot available in that zone (see Figure 2). The distance d to the zone is measured from the current location of the vehicle $e_k(\tau)$ and the arc closest to the centre of a zone, e_z. Within the selected zone, the arc with the largest number of free parking spots at the time step $\tau + \alpha h$ in that zone is selected to be $\widetilde{e_k}$. The vehicle will relocate to the pick-up location of that request and park there upon arrival. To ensure that this will be possible, a parking spot is reserved on arc e_q^o at the time of the selection of the location, to which the vehicle will relocate to.

In case that the pick-up location of none of the requests in $Q[\tau, \tau_h + \alpha h]$ is in a zone with a residual parking capacity, the vehicle will park in the zone closest to the vehicle with free parking. Again, the arc with the largest number of free parking spots at the current time step τ in that zone is selected to be $\widetilde{e_k}$.

Relocation Strategy "Supply Anticipation"

Another proactive relocation strategy is the anticipation of the vehicle supply in the network. This strategy aims at spreading out idle vehicles evenly over the system. This can improve the overall service performance and contributes to service availability in areas with low demand. Supply-anticipatory strategies require fleet regulation, as it hinders the direct competition between the drivers in one fleet. Taxi services with a larger fleet can be regulated according to this strategy by distributing taxis over different taxis stands. For on-demand transport services, this strategy has been simulated mostly on a zonal level (R. Zhang et al., 2016).

The strategy *Supply Anticipation* aims at an even dispersal of vehicles across the network based on the amount of available parking spots in the zones. For the time span between the current time step τ and the horizon time $\tau + \alpha h$, the expected number of parked idle vehicles per zone $K_z^{park}[\tau, \tau + \alpha h]$ is estimated, based on vehicle schedules and the current traffic state. Future scheduling decisions are not considered in this process. From the set of ζ zones with the least amount of parked vehicles expected at $\tau + \alpha h$, the zone z closest to the current position of the vehicle is chosen, under the condition that there is currently at least one free parking spot available in that zone, as formulated in Algorithm 2. Within that zone, the arc with the largest number of free parking spots at the time step $\tau + \alpha h$ in that zone is selected to be $\widetilde{e_k}$. Again, a parking spot for the vehicle is immediately reserved on that arc.

Table 5.1: Overview of the proactive idle vehicle relocation heuristics applied in simulation studies of fleets of on-demand transport and the Key Performance Indicators used to analyse them.

Study	Applied Relocation Strategy	Service Efficiency Indicators	Service Externality Indicators	Service Equity Indicators
Azevedo et al. 2016	Demand-Supply Balancing: Relocating of vehicles between stations to balance out supply and demand	Average passenger waiting time per person-trip	--	--
Babicheva et al. 2018	Demand Anticipation: Relocating of vehicles based on current and future demand at pick-up stations Demand-Supply Balancing: Reducing vehicle surplus or deficit at pick-up stations	Average and maximal passenger time per person-trip; total vehicle run-time	--	--
Bischoff and Maciejewski 2016	Supply anticipation: Hourly rebalancing of vehicles at pick-up stations based on anticipated supply deficit while minimizing costs of rebalancing trip	Average passenger waiting time per person-trip; Average vehicle utilisation (in hourly time shares)	--	--
van Engelen et al. 2018	Demand-Supply Balancing: Rebalancing of vehicles to balance out supply and demand	Average passenger waiting time per person-trip	Vehicle-Miles travelled (VMT);	Percentage of rejected requests
Fagnant and Kockelman 2014	Demand-Supply Balancing: Simulation of 4 strategies spreading idle vehicles out either according to “block balance” or move excess idle vehicle (any more than 2 per zone) to relocate to zones unoccupied by idle vehicles	Average passenger waiting time per person-trip; Average vehicle utilisation (in VMT)	Vehicle-Miles travelled (VMT); VMT caused by induced demand; Number of warm and cold starts per person-trip and per day	--
(Hörl et al., 2019)	Demand Anticipation: optimized relocation under full knowledge of future demand based on feedforward fluidic optimal rebalancing algorithm Supply & Demand Anticipation: Even distribution of vehicles during off-peak hours and demand anticipatory relocation during peak hours based on adaptive uniform rebalancing algorithm	Passenger waiting time per person-trip; fleet utilisation (active time per vehicle, empty mileage per vehicle); occupancy, operating time	Average speed, trip length per passenger	--
Sayarshad and Chow 2017	Demand-Supply Balancing: Simulation of a heuristics using queuing-based approximation on a zonal level, solved by Lagrangian decomposition	User cost and system cost measured in waiting time	--	--

Winter et al. 2017	Supply Anticipation: Based on heuristic to balance supply on a zonal level Demand Anticipation: Based on heuristic to anticipate demand on	Average passenger waiting time per person-trip; Average vehicle utilisation (in time shares)	Maximum parking demand per link; average parking duration	--
Zhang et al. 2015	Demand-Supply Balancing: Idle vehicles cruises for a couple of minutes in area with highest demand-supply deficit before parking there	Average passenger waiting time per person-trip	Average parking demand per SAV and daily parking demand of the total fleet	Spatial distribution of parking demand
Zhang and Pavone 2016	Demand-Supply Balancing: balance demand and supply per pick-up stations determined by k-means clustering	--	Congestion effects	--
Zhang et al. 2016	Cruising: Simulation of 1 algorithm randomly cruising idle vehicles; Demand Anticipation: 5 demand-anticipatory algorithms	Average passenger waiting time per person-trip	--	--

Relocation According to "Demand-Supply Deficit Minimization"
A third proactive strategy combines both perspectives by balancing demand and supply, which aims at balancing the anticipated demand and vehicle supply throughout the service area in order to ensure a high service efficiency. The implementation of this strategy requires fleet regulation in order to guarantee that drivers relocate to locations that are sub-optimal from the driver perspective, but optimal from the system perspective. Various heuristics and optimization approaches aiming at balancing the supply and demand have been simulated, most commonly either for pick-up stations or on a zonal level (Azevedo et al., 2016; Fagnant & Kockelman, 2014; Fagnant, Kockelman, & Bansal, 2015; Sayarshad & Chow, 2017; R. Zhang & Pavone, 2016; W. Zhang et al., 2015).

The strategy of *Demand-Supply Deficit Minimization* applied in this study is a combination of the two previous relocation strategies. Idle vehicles are sent towards the zone with the highest supply deficit in relation to anticipated demand. This deficit is defined as the number open requests occurring between the current time step τ and the horizon time $\tau + \alpha h$ in zone z, and the number of idle vehicles at $\tau + \alpha h$ in that zone, similar to the "balance value" applied in (W. Zhang et al., 2015). The zonal demand-supply deficit is based on the simplifying assumption that open requests located in zone z are dispatched to idle vehicles located within the same zone. This assumption is used in devising the relocation strategy and has no impact on the actual request-vehicle matching by the dispatcher at time step $\tau + \alpha h$.

To determine the deficit value, the number of potentially available vehicles is subtracted from the number of open requests for each zone. Out of the set of ζ zones with the largest predicted vehicle deficit, thus with the highest deficit value, at time step $\tau + \alpha h$, the one closest to the current vehicle location $e_k(\tau)$ is assigned as the destination zone z^* for the relocating vehicle. In case that no zone is predicted to have a vehicle deficit at $\tau + \alpha h$, the vehicle will relocate within zone z_k in which it is currently located. Within the target destination zone for relocation, the arc with the largest number of free parking spots in that zone is selected to be $\widetilde{e_k}$, as formulated in Algorithm 3. Again, a parking spot for the vehicle is reserved immediately on that arc. In case that none of the arcs in that zone has residual parking capacity, the vehicle is parked in the closest zone with free on the arc with the largest number of free parking spots at the current time step τ.

5.2.6 Performance and Level-of-Service Synthesis

There are several ways of assessing the performance of a relocation strategy, as shown in the overview of relevant literature in Table 1. Which strategy might be chosen depends on the objective that is formulated for services operated by the SAV. Different perspectives may be considered by the various stakeholders, such as the fleet operator, customers, municipalities tendering the on-demand transport services, other road users and residents of the city where such services are operated. The relocation of vehicles impacts the service efficiency, but also service externalities and service equity. Service efficiency can be defined from a user perspective (e.g in terms of average passenger waiting times per passenger trip) or from a supplier perspective (e.g. in terms of the ratio of vehicle–kilometres-travelled (VKT) without passengers on-board over the total VKT). The externalities of a service operated by SAV are the costs and benefits that affect those not making use of the service, which can be for example its contribution to congestion, undesired environmental effects or the use of public parking facilities. The equity dimension relates to the distribution of benefits and costs of the service over different population groups, notably as varying in their residential location. In terms of benefits, it relates to the variation in service quality as defined for instance in waiting times. In terms of costs, it relates to the distribution of congestion or the spatial pattern of the use of parking facilities. Table 5.1 provides a brief overview of simulation studies of on-demand transport fleets, the applied relocation strategies in these studies, and the key performance indicators employed in the assessment of the simulation results.

5.3 Case Study Application

As a simulation environment, the agent-based model MATSim has been used (Horni, Nagel, & Axhausen, 2016). The operation of the SAV has been simulated by applying the *Dynamic Transport Services* module of MATSim (Maciejewski, 2016). To analyse the impact of vehicle relocation strategies on the performance of SAV, the operation of SAV is simulated for a case study centred around the city of Amsterdam. The road network has been retrieved from openstreetmap.org (OpenStreetMap Contributors, 2018), by superposing a coarser network of arterial roads in the metropolitan area with a more detailed network within the city boundaries (Figure 5.3a). For analysing the spatial impacts of the different relocation strategies, the municipal area has been divided into zones based on the 4-digit postal codes, resulting in 82 zones, as shown in Figure 5.3b. The zones used for the relocation strategies are thus not equal in terms of size, population, and parking facilities. However, also the current parking zone in the city of Amsterdam is based on the 4-digit postal code division for residential on-street parking, and on a clustering of 4-digit postal codes, grouped to 21 different parking zones, for general on-street parking. For this reason, we use the zonal division by 4-digit postal codes as an input parameter to our simulation study as well.

In the following, we describe in more detail the set-up of the simulated scenario, in particular in regard to the simulated agents, their behaviour and their usage of SAV. An overview of all specifications of the Amsterdam scenario is shown in Table 5.3.

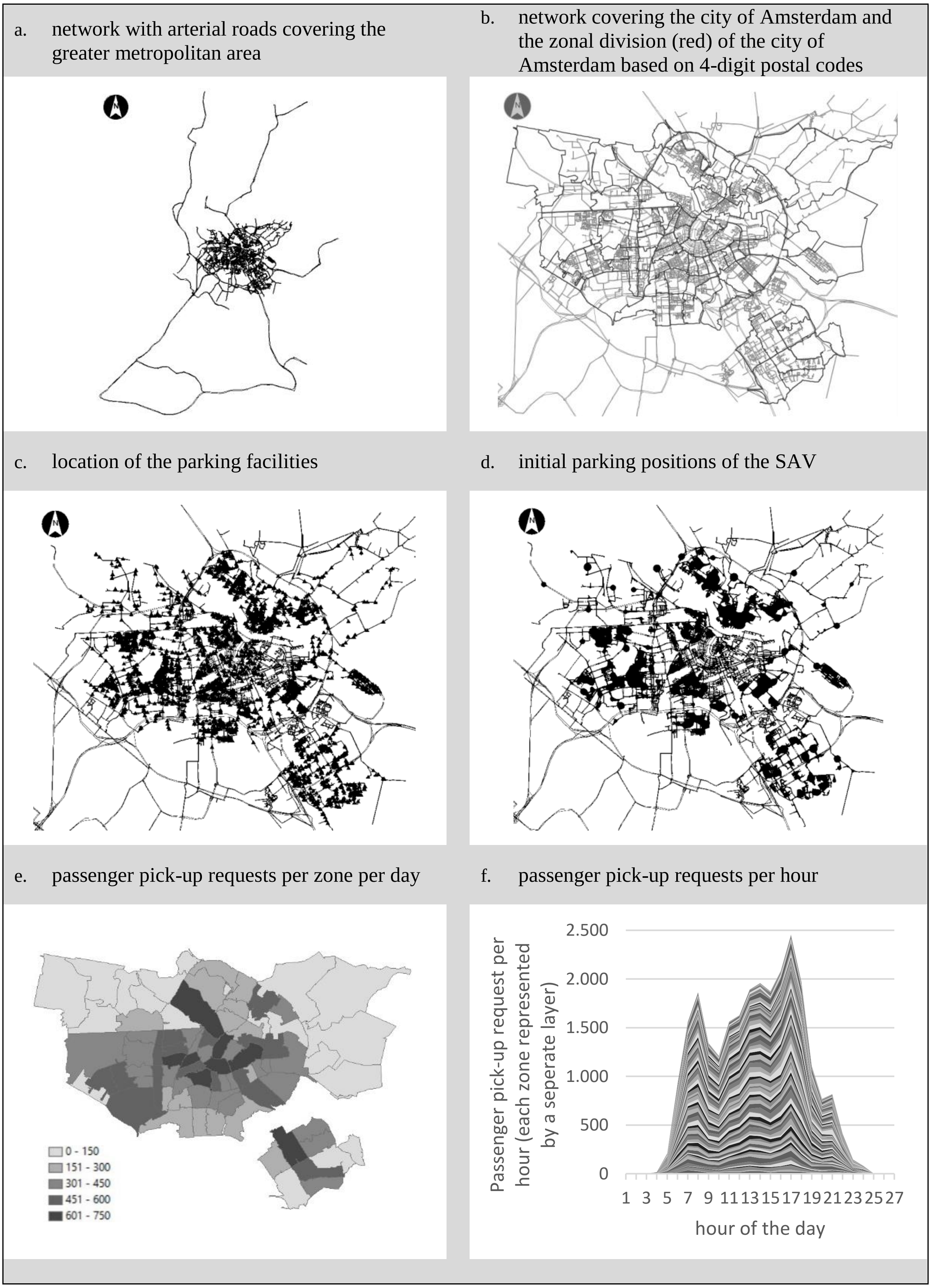


Figure 5.3: a) Network, b) zones, c) parking spots d) and initial parking location of the SAV, as well as of the simulated case study of Amsterdam, as well as the e) number of passenger pick-up requests of the simulated day per zone and f) passenger pickup requests per hour (each layer represents a zone).

Table 5.2: The 'Amsterdam MATSim-Scenario' at a glance.

1. Network & Geography			
Number of simulated agents (represented by 20%)	767,495		
Network: number of links	31,131		
Network: number of nodes	17,385		
Area size: greater metropolitan area [in km^2]	50,888		
Area size: core city (= service area of the SAV) [in km^2]	211		
Number of zones covering the core city (= service area of the SAV)	82		
2. Specified Behavioural Model of the MATSim Agents	**phase 1**	**phase 2**	**final run**
routing algorithm	Dijkstra		
coefficient for the utility of performing an activity ($\beta_{duration}$)	16.25		
coefficient for arriving late is weighed ($\beta_{late\_arrival}$)	-48.75		
maximum plan memory of agents	5	3	1
fraction of iterations after which plan innovation is disabled and score convergence is enabled [in %]	85	100	100
plan selection based on utility model [in %]	70	70	90
plan innovations based on re-routing for car trips [in %]	10	5	5
plan innovations based on changed departure time (±15 minutes) [in %]	5	5	5
plan innovations based on changed single trip modes [in %]	10	10	0
plan innovations based on changed sub-tour modes [in %]	5	10	0
number of simulation runs	75	15	2
➔ resulting modal share for SAV [in %]	4.5	4.3	4.3
3. Mode Options and Specifications			
modes simulated by teleportation	walk, bike, public transport		
beeline distance factor for teleportation	1.3		
teleportation speed: walking [in km/h]	5		
teleportation speed: cycling [in km/h]	15		
teleportation speed: public transport	freespeed car travel[3]		
number of simulated SAV (represented by 20%)	12,500		
number of parking spots dedicated for SAV (represented by 20%)	15,000		
MATSim-specific dispatching algorithm for SAV	"rule-based"		
re-optimization time step for SAV [in seconds]	60		
pick-up time for SAV [in seconds]	120		
drop-off time for SAV [in seconds]	60		
4. Average simulation runtime of 1 full day on desktop PC with Intel Core i5-3470 3.2 GHz, 16GB RAM; including replanning phase and dumping of output files			
without SAV [in seconds]	308		
with SAV, no relocation [in seconds]	648		
with SAV, "Demand-Anticipation" [in seconds]	1,715		
with SAV, "Supply-Anticipation" [in seconds]	23,043		
with SAV, "Demand-Supply-Balancing" [in seconds]	21,892		

[3] Differing to the MATSim default setting, the "teleportedModeFreespeedFactor" for the ratio between car speed and public transport speed has been set to 1.

5.3.1 Travel Demand

The daily activity plans of the agents travelling within the case study network have been specified based on the outcome of the Dutch activity-based model ALBATROSS for the base year 2004 (Arentze & Timmermans, 2004). Its outcome is a travel demand model specifying the activities performed by each member of a household, including i.a. the start time and end time of the activity, the 4-digit postal code of the activity and the chosen travel mode to reach the activity location. The Dutch 4-digit postal code areas are quite large (see zonal division shown in Figure 5.3). For this reason, we attributed to each activity an actual address within the postal code area at random. The ALBATROSS data set has been reduced to households in which at least one household member performs at least one activity within the municipality of Amsterdam. For computational reasons, we simulate only 20% of the population, therefore each agent is weighted by a factor of five in the simulation. In doing so, we follow common practice (see also Maciejewski and Bischoff, 2016). This results in a total of 767,495 agents (represented by 153,499) who perform a total of 3,776,805 activities on a single day and move either by car, public transport or active mode (walking and cycling combined). The majority of the agents are based in Amsterdam, but a substantial share arrives from surrounding suburbs and from nearby towns situated in the greater metropolitan area. The altered data set used in this study and a detailed description of how it has been derived is publically available (see Winter and Narayan, 2019).

5.3.2 Specification of SAV and Their Infrastructure Needs

Since automated on-demand transport services are not operational as of now, assumptions concerning their operational and technical specifications, as well as the assumptions on the passengers' reception of such services remain speculative for the moment. For this reason, a simple scenario has been drawn regarding the technical and operational specification of SAV and their according infrastructural needs. The assumptions made on AV technology and infrastructure needs are reduced in complexity so that the simulation results remain traceable and the analytical focus can be put on the relocation strategies.

In this study, SAV are offered as an additional mode alternative to private car, public transport and active modes. In terms of vehicle technology, SAV are regarded to be similar in their performance to private cars, they achieve thus the same driving speeds and have the same physical dimensions. In this study, SAV and private cars share the same road infrastructure, it is such a simulation of mixed traffic. In operational terms, the SAV are assumed to be operated as a centrally dispatched fleet which allows for sequential vehicle sharing. Car-pooling, i.e. simultaneous vehicle sharing, is thus not considered in this study. Vehicles are assumed to fully comply to the dispatcher and operate in a collaborative scheme. In regard to their infrastructural needs, it is assumed that they share the road infrastructure built for private cars and can drive on all links of the road network.

To test the impact of the different relocation strategies, the fleet size has been set to 12,500 vehicles, which leads to an average passenger-waiting time of 4 minutes – a value which we selected to represent an acceptable level of service. This fleet size for SAV is approximately 2% of the simulated fleet size of private vehicles. For these vehicles, 15,000 curbside parking spots are reserved throughout the network within the limits of the city area, their location is shown in Figure 5.3c. We generated these parking spots per link-arc based on the link length, which therefore determines the storage capacities for idle vehicles per link. These generated parking spots are located in the middle of arcs representing residential streets situated within the city boundaries on streets with a maximum allowed speed of 50 km/h. At the beginning of the simulated day, the SAV are parked randomly on the dedicated parking facilities, as shown in Figure 5.3d. The amount of dedicated parking spots has been selected so that sufficient parking space is provided to the SAV at all times throughout the simulation, and so that in addition some extra space is available to efficiently park the vehicles according to the relocation strategies. In this scenario, parking spots can be allocated and reserved by the same central dispatcher, who also performs the request dispatching. We capped the size of the set of candidate zones considered for relocation to three (ζ=3).

5.3.3 Behavioural Model and Model Specifications

The modal split present in the reduced ALBATROSS data set is not aligned with the modal split observed for the city of Amsterdam based on all trips taken within the city as well as trips with either their origin or destination within the city boundaries (Gemeente Amsterdam, 2016). To overcome this, the plans of the agents have been calibrated by simulation based on the co-evolutionary learning process implemented in MATSim until a modal split similar to the one observed for the city of Amsterdam (including walking and cycling, which account for large shares of trips performed) has been achieved. The calibration has been performed under the conditions that the daily travel pattern remains showing two demand peaks due to commuting and that all agents reach their final destination within the simulated period. While the Amsterdam scenario has been carefully calibrated to reproduce the actual local overall modal shares, the simulated scenario has not been calibrated for more detailed traffic and travel data.

Over time, MATSim agents can alter their daily plans following a set of day-to-day learning rules. The MATSim-specific settings in regard to this simulated learning-behaviour are presented in Table 5.3. After a completed simulation run of one day, agents either select their next plan from a set of plans they have memorized from previous simulation runs based on the plans' scores, or alter parts of their plan according to pre-defined plan-innovation rules (see Table 5.3). The learning behaviour simulated in MATSim is based on the concept of utility. The utility of performing an activity is described by the activity duration, the waiting time in case of arriving too early, a potential delay, a potential early departure and the potential reduction of the desired time spend on the activity (Nagel et al., 2016). The coefficient for the utility of performing an activity, $\beta_{duration}$ is based on the value of the average hourly wage in Amsterdam in the year 2017, which is 16.25 Euro per hour (Gemeente Amsterdam, 2018b). The coefficient for arriving late is weighed three times as much as $\beta_{duration}$, following the standard MATSim settings and the findings in Börjesson et al. (2012). The disutility of travelling depends on travel time and travel costs. The coefficient for travel time $\beta_{travel\_time,m}$ is mode specific, while the one for travel cost β_{travel_cost} is generic, based on the assumption that costs are perceived in a rational manner. Additional mode-specific preferences are represented by the *Alternative Specific Constants* (ASC_m). The cost parameters and the mode-specific constants for travel time for the modes car, public transport, cycling and walking as well as the cost parameters are, where possible, based on values reported in literature (K. van Ommeren, Lelieveld, de Pater, & Goedhart, 2012) and are presented Table 5.2.

The values for $cost_{SAV}$ are based on values reported for the simulation of comparable services, which range between 14 €-cent/km and 91 €-cent/km, with most studies settling at price similar to the one used in our study (see Bösch et al. 2018; Gurumurthy et al. 2019; Simoni et al. 2019). The values for the perceived utility of SAV have been set to be the same as the ones for private car, since the way we envision this transport service is most similar to the one of the mode "car" in this model: passengers are moved inside a motorized vehicle, which is not shared with strangers, and provides an on-demand door-to-door transport service. Currently the state-of-the-art discrete choice models comprising the choice between SAV and the other modes included in this model are not unequivocally enough to make an assertive statement about the relative difference in the perceived utility of SAV and car (Ashkrof, Correia, Cats, & van Arem, 2019; de Looff, Correia, van Cranenburgh, Snelder, & van Arem, 2018; Simoni et al., 2019). However, the specified behavioural model serves the purpose of creating a test-bed in which strategies for idle vehicle relocation for SAV can be analysed in regard to their service efficiency, externalities and equity. This can be achieved with the simplified model described in Table 5.2 and Table 5.3. Nevertheless, given the many uncertainties linked to the user preferences towards vehicle automation in general, and shared automated vehicles in particular, we refrain from analysing the impact of the relocation strategies on mode shifts and mode shares. The latter should be included in such an analysis once more reliable mode-choice models for SAV are available.

Table 5.3: Constants and coefficients specified for the utility function formulating the mode choice behaviour of the agents

Mode	$ASC_{m(q)}$	$\beta_{travel\_time,m(q)}$	β_{travel_cost}	$cost_q$
Car	0.0	-10.7	1	30 €-cent/km
Public Transport	-8.3	-6.65	1	25 €-cent/km
Cycling	-1.0	-10.7	1	0 €-cent/km
Walking	0.3	-6.65	1	0 €-cent/km
SAV	0.0	-10.7	1	30 €-cent/km

For this reason, we suppressed mode changes in the final model used to test the relocation strategies. To able to do so, we split the simulation process into three parts: (1) In the first calibration phase, we let agents incorporate SAV into their daily plans in the course of 76 repeated simulations of one day. During the cause of these simulated days, agent mode choice behaviour stabilized, leading to a modal share of 4% for SAV, which equals approximately 130,000 trips performed using SAV per day (Table 5.3). (2) The resulting plans of the final simulated day have been used as an input in the second simulation phase, in which the same day has been simulated in 16 runs. (3) The output of this second round has been used as an input for the final simulation, in which the same day is simulated only twice, while suppressing any mode choice innovations. The second simulation phase has proven to be necessary due to a particular feature inherent to MATSim's *Dynamic Transport Services* module, which uses the exponential moving averages of link travel times over all iterations of a simulation for its dispatching algorithm. Without the intermediate step, the output of the last day of the first calibration phase would not lead to the same results of the first day of the final simulation. The applied solution to this problem has also been suggested in (Maciejewski & Bischoff, 2018). The demand for SAV is shown on a zonal level in Figure 5.3e, the temporal distribution of the requests for SAV are shown in Figure 5.3f, in which the requests per hour per zone are stacked up on top of each other in layers.

During the learning phase of the agents, the relocation strategy of "demand-anticipation" has been applied to capture the appropriate agent learning behaviour as a response to SAV service that is subject to parking restrictions. We opted for this strategy for computational reasons, as this strategy shows the shortest computational times (see Table 3). The resulting plans of this simulation are used as an input to all following simulations testing the different relocation strategies. The input the scenarios simulating the different relocation studies is thus the output of the simulations performed in the initialisation phases. It contains a set of agents and their activity schedules for the simulated day, including their travel behaviour. For the simulation of the relocation strategies for SAV, these plans are not altered any further, the demand for SAV is thus kept inelastic.

5.4 Results

In the following, the results for the three relocation strategies of *Demand Anticipation*, *Supply Anticipation* and *Demand-Supply Balancing* are assessed for three categories of key-performance indicators (KPI): (1) service efficiency, (2) service externalities and (3) the service provision equity. We also include into this discussion the results for the scenario *Remain*, for which vehicles simply wait at their latest drop-off location, irrespective of the availability of parking facilities. The *Remain* scenario is thus not a valid representation of the real-life constraints caused by the scarcity of road-space and parking-space. For this reason, we focus on the comparison between the three scenarios in which idle vehicles have to relocate according to one of the relocation heuristics (*Demand Anticipation*, *Supply Anticipation* and *Demand-Supply Balancing*), and not on the comparison between a situation with and without the relocation of idle vehicles[4]. However, we provide results for the scenario *Remain* in order to allow a comparison also to other simulation studies of SAV with this feature. All discussed KPI are based on the average results of 4 runs. The number of necessary runs per relocation strategy has been determined by a two-sided t-test between means with a 95% confidence interval.

5.4.1 Service Efficiency

The service efficiency is measured in KPI describing the quality of service from a passenger's perspective, as well as KPI showing how efficiently the transport service can be operated. For an overview of these KPI, see Table 5.4, as well as Figure 5.4 and 5.5.

Table 5.4: Key Performance Indicators regarding the service efficiency for the relocating strategies Demand Anticipation, Supply Anticipation and Demand-Supply Balancing.

	Demand Anticipation	***Supply Anticipation***	***Demand-Supply Balancing***
Share of empty driven mileage over total driven mileage: $\frac{\boldsymbol{VKT_{SAV\_empty}}}{\boldsymbol{VKT_{SAV}}}$ [**in** %]	56.1	57.1	57.1
Share of driven mileage for relocation over total empty driven mileage: $\frac{\boldsymbol{VKT_{SAV\_relocating}}}{\boldsymbol{VKT_{SAV\_empty}}}$ [**in** %]	70.5	75.0	75.2
Share of time driven emptily: $\frac{\boldsymbol{tt_{SAV\_empty}}}{\boldsymbol{tt_{total}}}$ [**in** %]	14.0	14.5	14.6
Average in-vehicle times per trip in SAV: $\boldsymbol{ivt_{SAV}}$ $[\boldsymbol{min}]$	18.0	18.4	18.2
Average and 95% percentile of passenger waiting time: $\boldsymbol{t_{SAV\_wait}}$; $\boldsymbol{t_{SAV\_wait\_95\%}}$ $[\boldsymbol{min}]$	4.6 ; 12.1	3.6 ; 9.4	3.5 ; 9.1

[4] For such a comparison, see the juxtaposition of the results for all simulated relocation strategies presented in the Appendix.

Waiting Times

The average passenger waiting time t_{SAV_wait} is with 3.5 minutes the lowest for the strategy *Demand-Supply Balancing*. The highest average waiting time with 4.6 minutes occurs for the strategy *Demand Anticipation*. The average waiting time for the *Supply Anticipation* strategy lies with 3.6 minutes close to the one of the *Demand-Supply Balancing* strategy. All three relocation strategies increase the passenger waiting times in comparison to the *Remain* scenario, for which the average passenger waiting time is 2.2 minutes. In regard to 95% percentile of the passenger waiting times $t_{SAV\_wait\_95\%}$, the same trend than for the average passenger waiting time can be observed: with 12.1 minutes the highest value is reached for the strategy *Demand Anticipation*, with 9.1 minutes the lowest value for the strategy *Demand-Supply Balancing*, closely followed by the one for *Supply Anticipation*.

We did not set a cap on the maximum waiting times, therefore no requests have been declined or cancelled by passengers. This leads to a maximum passenger waiting time of 189 minutes in the scenario *Remain*. For the scenarios with idle vehicle relocation, the longest maximum passenger waiting time is reached for the strategy *Supply Anticipation* (278 minutes), followed by the strategy *Demand Anticipation* (271 minutes) and *Demand-Supply Balancing* (252 minutes). These very long waiting times cannot be interpreted as the expected maximum waiting times for an on-demand service operated by SAV, as it is not realistic that passengers would wait several hours for their ride to arrive. But these values show the extent to which the different strategy disadvantage passengers in different areas, which is discussed in more detail in the following sections.

Empty Driven Mileage

The total driven mileage for a fleet of SAV is composed of the VKT with passengers on-board as well as VKT driven emptily. The ratio between the VKT with and without passengers on-board is an important KPI for the efficiency of the service. In our scenario, the average trip length for trips taken in SAV is approximately 12 kilometres, but the total VKT travelled per trip is a threefold of this once idle vehicle relocation is introduced. In the course of a day, SAV are driving emptily (VKT_{SAV_empty}) for two different purposes: (a) moving from the latest drop-off location to the assigned parking spot leads to empty VKT due to relocation ($VKT_{SAV\_relocating}$) and (b) moving from to the parking spot to the next pick-up location. A leading KPI to measure the efficiency of the operation of an SAV service is the share is of the empty driven mileage VKT_{SAV_empty} of the total driven mileage VKT_{SAV}, which varies between 56.1% and 57.1% for all three relocation strategies. If vehicles are not relocated, as simulated in the scenario *Remain*, this ratio drops to 10.2%.

When looking in more detail at what causes the empty VKT, it can be observed that the relocation strategy *Demand Anticipation* has with 70.5% the lowest share of empty VKT for relocating vehicles $VKT_{SAV\_relocating}$, and thus, conversely, has the highest shares of empty VKT for approaching passengers at their respective pick-up locations. The strategies *Supply Anticipation* and *Demand-Supply Balancing* have with 75.0% and 75%, respectively, a higher share of empty VKT caused by relocation, and conversely fewer empty VKT caused by moving from their parking location to the pick-up locations of their next customer.

Trip Times

The time for a trip in an SAV experienced by a passenger is a combination of waiting time, the time it takes to enter the vehicle (set to 120 seconds in the simulation), the in-vehicle time and the time it takes to exit the vehicle (set to 60 seconds in the simulation). For the scenario

Remain, the average in-vehicle time per trip (ivt_{SAV}) is 15.4 minutes, and the average trip time is 20.6 minutes. When introducing idle vehicle relocation, the average trip times increase by factor 1.2, with *Demand-Supply Balancing* leading to an average trip time of 24.8 minutes, followed by *Supply Anticipation* (25.0 minutes) and *Demand Anticipation* (25.3 minutes). The difference in trip time between the strategy *Demand Anticipation* and *Demand-Supply Balancing* is 57 seconds, which translates in our scenario to a difference of 2042 passenger-hours saved for users of the SAV in case of the strategy *Demand-Supply Balancing.* The differences in in-vehicle time originate solely from different levels of congestion, which is discussed in more detail in the following sections, since the demand is kept inelastic for the analysed case study.

Service Efficiency: Summary

Concerning service efficiency, it can be concluded that the strategy *Demand-Supply Balancing* leads to the shortest average passenger waiting times, which also leads to the shortest total trip times for the simulated case study. This comes however at the cost of longer in-vehicle travel times, which are a result of congestion effects caused by relocating vehicle to areas with high demand, as well as congestion elsewhere in the network due to vehicles spreading out in zones with an undersupply of vehicles. These local congestion effects due to vehicle bunching are the strongest for the strategy *Demand Anticipation,* which is also the strategy with the longest average passenger waiting time. However, when it comes to the shares of empty driven mileage or the time spend on relocating, is the strategy *Demand Anticipation* the most efficient for the simulated case study, and the strategy *Demand-Supply Anticipation* the least efficient one.

Table 5.5: Key Performance Indicators regarding the service externalities for the relocating strategies Demand Anticipation, Supply Anticipation and Demand-Supply Balancing.

	Demand Anticipation	***Supply Anticipation***	***Demand-Supply Balancing***
Average driving speed for SAV: v_{SAV} $\left[\frac{km}{h}\right]$	39.2	39.2	39.1
Average driving speed of SAV with and without passengers on-board: v_{SAV_IVT} ; v_{SAV_empty} $\left[\frac{km}{h}\right]$	38.9; 39.6	39.3; 39.1	39.0; 39.2
Total mileage of SAV: VKT_{SAV} $[in\ 1000\ km]$	3,519	3,610	3,608

5.4.2 Service Externalities

The externalities of SAV relocation strategies are analysed for three aspects: (1) the average driving speed as a proxy for congestion, (2) the total driven mileage as a proxy for energy consumption and potential emissions and (3) the spatial consumption of curbside parking space by SAV. For an overview of these KPI, see Table 5.5.

Congestion

As already pointed out in the previous section, the different relocation strategies lead to different levels of congestion. In this simulation, potential congestion effects caused by pick-up and drop-off situation or potential lower flow density caused by mixed traffic with automated and non-automated vehicles are not included, and the presented values might be therefore an underestimation of congestion SAV might cause.

The average driving speed of the SAV (v_{SAV}) in the scenario *Remain* is 46.4 km/h. When forcing vehicles to relocate when idle, the v_{SAV} goes down by about 17% (see Table 5.5). Using the average speed as a proxy for congestion, it can be concluded that vehicle relocation causes undesired externalities in the form of additional disturbances in the network flows. To understand better, how and where the different relocation strategies can cause congestion, we analyse the driving speeds of SAV with and without passengers on-board separately. The average driving speed for SAV for the scenario *Remain* is 46.0 km/h with passengers on board (v_{SAV_IVT}) and 50.0 km/h without passenger on board (v_{SAV_empty}). When introducing idle vehicle relocation, in particular v_{SAV_empty} goes down (roughly by 25% for all relocation strategies compared to the scenario *Remain*), indicating that vehicles driving empty to and from their parking locations experience (and create) more congestion than those serving passenger request. The impact on v_{SAV_IVT} on the other hand is less strong, with the percentage difference being approximately 15% for all strategies compared to the scenario *Remain*. Looking in more detail at the differences between the relocation strategies, it can be observed that for the strategies that relocate idle vehicles closer to anticipated future demand (*Demand Anticipation* and *Demand-Supply Balancing*), v_{SAV_empty} is faster than v_{SAV_IVT}, and that the differences between these two speeds are more pronounced than for the strategy *Supply Anticipation.* This is a direct result of the boundaries set by the relocation algorithms, which leads in the case of anticipated demand to vehicle accumulation in the areas with the highest demand levels. As a consequence, idle vehicles are blocking each other when departing from the zones with high demand. The strategy *Supply Anticipation*, on the other hand, creates less of locally concentrated congestion, but slows down traffic flows more evenly in the network. The strategy *Demand-Supply Balancing* combines, in regard to congestion effects, the worst of both strategies and leads consequently to the lowest average driving speed.

Driven Mileage

In this study, the discussion of the effects of vehicle relocation of SAV on energy consumption and emissions is deliberately kept on an abstract level. No assumptions on the source of vehicle propulsion for the SAV is made, thus also no assumption on the magnitude of energy consumption, fine dust matter in the form tyre debris (see Kole et al. 2017), noise pollution (see Campello-Vicente et al. 2017) or other emissions can be made. The impact of the relocation strategies is instead based on the total driven mileage as a proxy, which can be used as input to any traffic emission estimation model. The total mileage driven by SAV is presented in Table 5.5.

For the scenario *Remain,* the total VKT_{SAV} for the entire fleet is 1,707,415 km, which corresponds to an average of 13.2 km driven per trip served by SAV. When introducing idle vehicle relocation, the total VKT increase with more than factor 2. When applying the strategy *Demand Anticipation,* the total VKT_{SAV} is 3,518,975 km, translating to 27.2 km driven per served passenger trip. The strategies aiming at spreading out idle vehicles more increase the total driven mileage even further, with VKT_{SAV}=3,609,493 km for the strategy *Supply Anticipation* and VKT_{SAV}=3,607,769 km for the strategy *Demand-Supply Balancing,* translating to approximately 27.9 km driven per served passenger trip. The results of these additionally VKT are overall lower driving speeds, as discussed in the previous section.

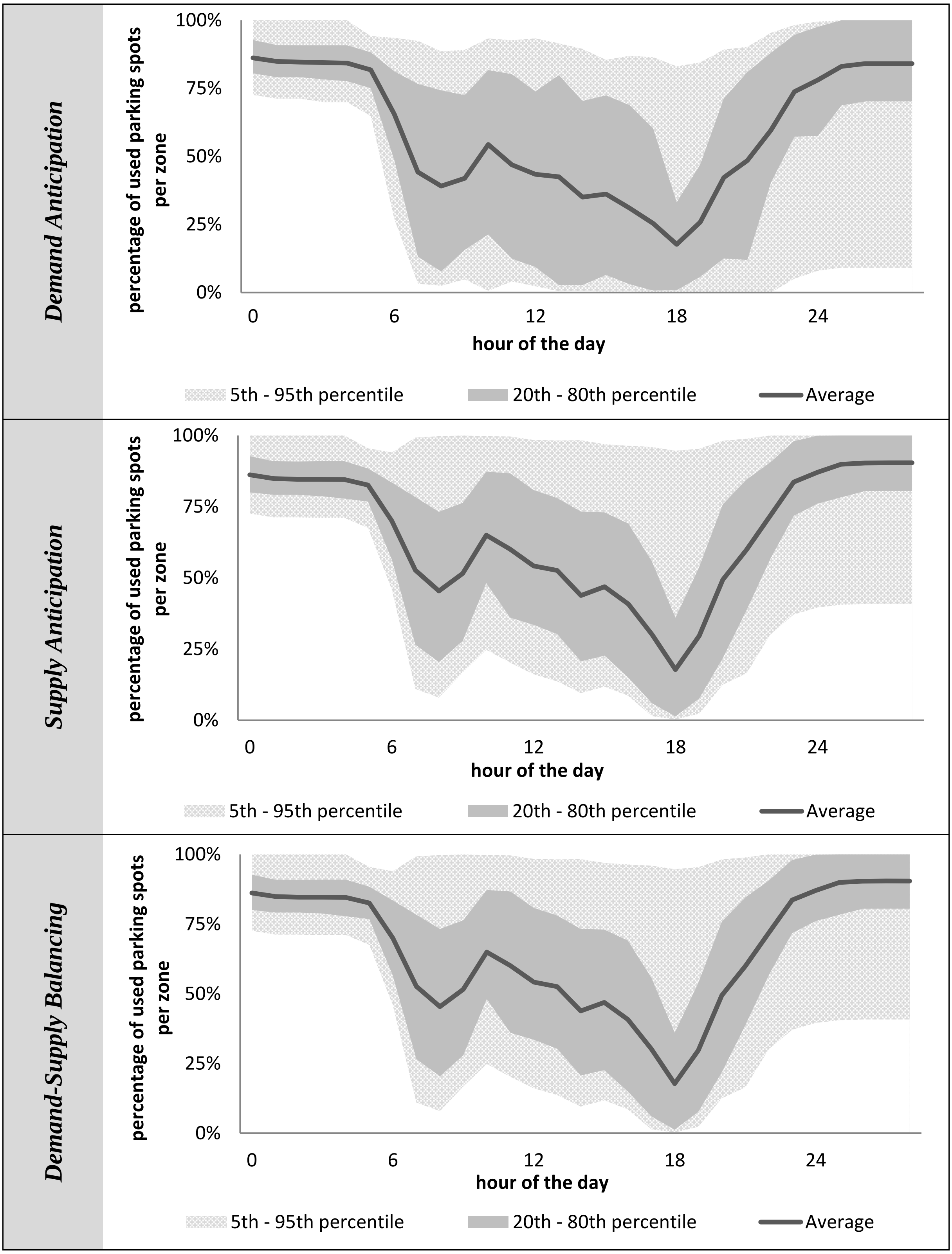


Figure 5.4: Average zonal parking usage (solid line) over the course of a simulated day. The 5th-95th percentile and 20th-80th percentile is shown by the shaded areas.

Parking Space Consumption

As a third aspect of service externalities, the curbside parking consumption is analysed. This analysis is conducted at a zonal level. For each zone, the parking space utilisation rate has been determined on a minute basis and is averaged per hour, allowing to trace the parking use over time.

In Figure 5.4, the course of the hourly parking usage averaged over all zones is shown. The average parking usage follows a similar pattern over the course of the day for the three relocation strategies, and averages to about 65% for all strategies for the whole day. However, the distribution of the parking usages for the strategy *Demand Anticipation* differs strongly to the one for the strategies *Supply Anticipation* and *Demand-Supply Anticipation,* which can be clearly seen when comparing the range of the 5^{th} – 95^{th} percentile and the 20^{th} – 80^{th} percentile. When applying *Demand Anticipation*, the spatial distribution of idle vehicles follows the demand patterns simulated in the case study, which is not evenly distributed, as shown in Figure 5.3e and f. This leads to parking facilities in zones with high demand getting fully used, while parking spots in zones with lower demand remain unused. This effect is particularly strong during the off-peak hours, thus the periods in which most vehicle relocations happen, the variance in spatial distribution increases further.

Parking Space Consumption

As a third aspect of service externalities, the curbside parking consumption is analysed. This analysis is conducted at a zonal level. For each zone, the parking space utilisation rate has been determined on a minute basis and is averaged per hour, allowing to trace the parking use over time.

In Figure 5.4, the course of the hourly parking usage averaged over all zones is shown. The average parking usage follows a similar pattern over the course of the day for the three relocation strategies, and averages to about 65% for all strategies for the whole day. However, the distribution of the parking usages for the strategy *Demand Anticipation* differs strongly to the one for the strategies *Supply Anticipation* and *Demand-Supply Anticipation,* which can be clearly seen when comparing the range of the 5^{th} – 95^{th} percentile and the 20^{th} – 80^{th} percentile. When applying *Demand Anticipation*, the spatial distribution of idle vehicles follows the demand patterns simulated in the case study, which is not evenly distributed, as shown in Figure 5.3e and f. This leads to parking facilities in zones with high demand getting fully used, while parking spots in zones with lower demand remain unused. This effect is particularly strong during the off-peak hours, thus the periods in which most vehicle relocations happen, the variance in spatial distribution increases further.

The parking usage depends on the shape, size and parking capacity of the zones, and is thus case-specific. For this reason, it is important to not just look at the average usage over zones and its respective variance, but also look at the distribution of zonal waiting times in the heat maps shown in Figure 5.5. These show that the strategy *Demand Anticipation* leads to a more unbalanced distribution of parked vehicles throughout the city than the other two strategies by concentrating idle SAV in high-demand areas in the North of the city, following the demand pattern shown in Figure 5.3e.

In Figure 5.5, the hourly average of parking usage is shown for two moments in time: the initial parking usage in the first hour of the simulated day and the parking usage after the evening peak in the 21^{st} hour of the simulated day. The strategy *Demand Anticipation* leads to more parked vehicles in the centre and the West of the city, while *Supply Anticipation* and *Demand-Supply Balancing* lead to more parked vehicles in the South and East of the city, and overall to a more even distribution of idle vehicles in the city area.

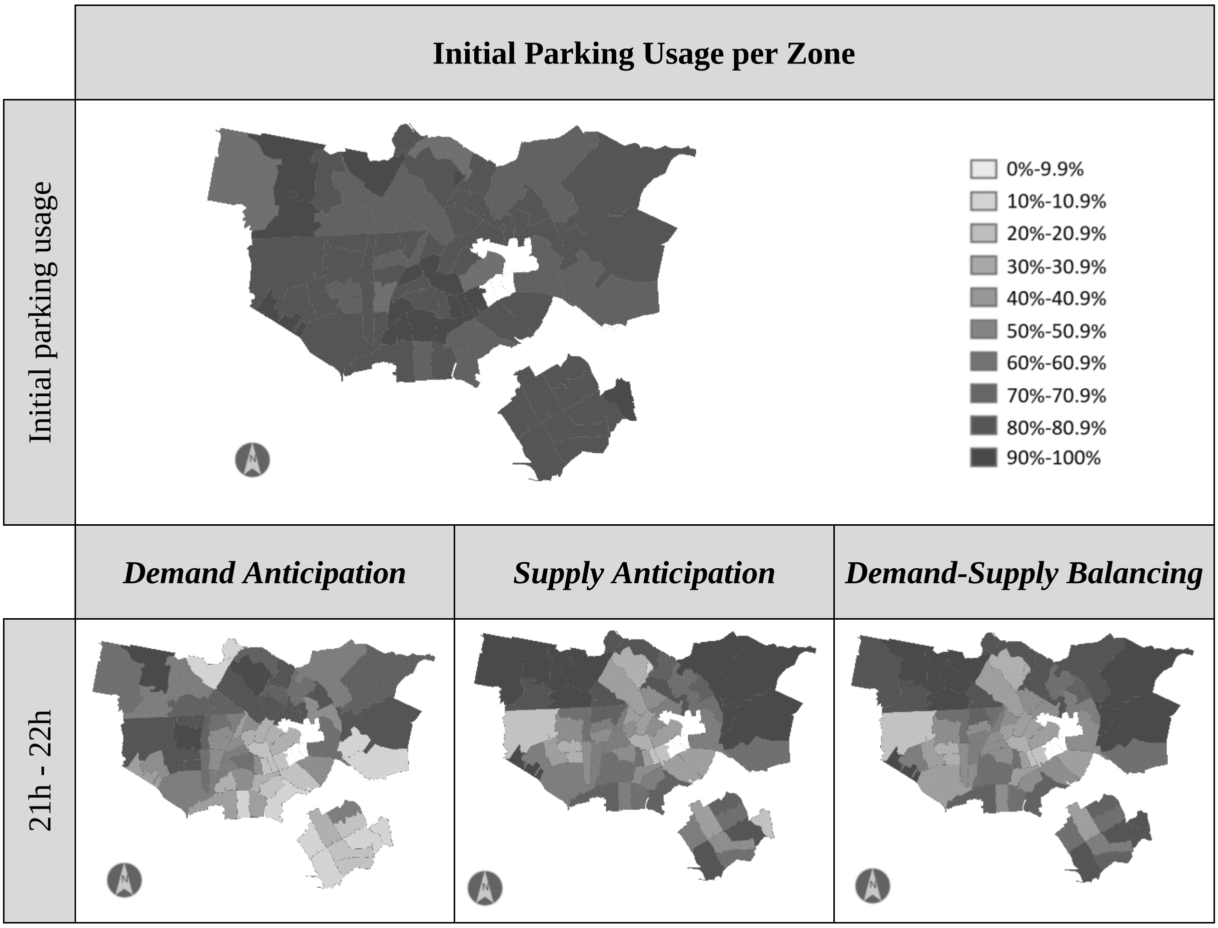


Figure 5.5: Zonal parking space utilization rate for the three relocating strategies Demand Anticipation, Supply Anticipation and Demand-Supply Balancing after the evening peak hour (21h-22h). The initial parking usage per zone is shown at the top.

Service Externalities: Summary
In regard to undesired externalities, it can be concluded that the strategy *Demand Anticipation* leads idle vehicle congregating in high demand areas and thus causes local congestion and an uneven usage of the parking facilities, but also creates less congestion in the network overall and contributes the least to energy consumption and emissions. The strategy *Demand-Supply Balancing,* on the other hand, is less favourable for reducing undesired emissions and contributes more to congestion in the network than *Demand Anticipation.* The strategy *Supply Anticipation* causes the highest number of VKT, but outperforms the strategy *Demand-Supply Balancing* in regard to congestion, as this strategy causes less local congestion than the other two strategies anticipating future demand.

5.4.3 Service Provision Equity

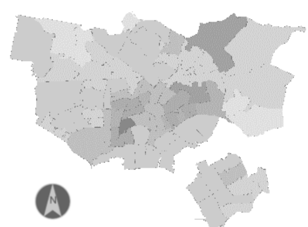
In regard to undesired externalities, it can be concluded that the strategy *Demand Anticipation* leads idle vehicle congregating in high demand areas and thus causes local congestion and an uneven usage of the parking facilities, but also creates less congestion in the network overall and contributes the least to energy consumption and emissions. The strategy *Demand-Supply Balancing,* on the other hand, is less favourable for reducing undesired emissions and contributes more to congestion in the network than *Demand Anticipation.* The strategy *Supply Anticipation* causes the highest number of VKT, but outperforms the strategy *Demand-Supply*

Balancing in regard to congestion, as this strategy causes less local congestion than the other two strategies anticipating future demand.

Waiting Time Distribution

The Gini-index for the passenger waiting times G_{wait} for the scenario *Remain* is 0.453, and for the average zonal passenger waiting times $G_{wait,z}$, the Gini-index is 0.215. For the scenarios with idle vehicle relocation, the highest Gini-index, and thus the most unequal distribution for passenger waiting times occurs when applying the strategy *Demand Anticipation* (G_{wait} = 0.554). This is also the strategy that leads to the longest average waiting times (Table 5.4), which shows that the gains in overall reduced waiting times by placing vehicles strategically in anticipation of future demand not only comes at the cost of overall longer waiting times for passengers, but that these are also particularly unequally distributed by systematically disadvantaging passengers in zones with lower demand. This can be also be seen in the spatial representation of averaged waiting times, where it obvious that passengers in the West of the city benefit from shorter average zonal waiting times compared with those in the North-East and South. The lowest Gini-coefficient for the total waiting times is achieved with the strategy *Demand-Supply Anticipation*, which is also the strategy leading to the lowest average waiting times (Table 5.4). In the simulated case study, a more equal distribution of all waiting times leads thus to higher efficiency in the service operation in regard to average waiting times.

Table 5.6: Key Performance Indicators regarding the service equity for the three relocating strategies Demand Anticipation, Supply Anticipation and Demand-Supply Balancing. Zones for which no demand occurs are left blank.

	Demand Anticipation	***Supply Anticipation***	***Demand-Supply Balancing***
Gini-coefficient for passenger waiting times G_{wait}	0.554	0.517	0.507
Gini-coefficient for average zonal passenger waiting times $G_{wait,z}$	0.291	0.276	0.265
Zonal average waiting times [in minutes] 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 min 8-8.9 min 9-9.9 min 10-10.9 min 11-11.9 min 12-12.9 min 13-14 min			

Service Provision Equity: Summary

Regarding the service provision equity, it can be concluded that while the strategy *Demand Anticipation* leads to the shortest waiting times in average, it also leads to the least equal waiting times. When positioning idle vehicles close to future requests, the short approach times which can be achieved for a large groups come at the cost a few who experience very long waiting times. More equally distributed waiting times can be achieved for strategies that aim spreading out idle vehicles more, such as *Demand-Supply Balancing* and in particular *Supply Balancing*. This however leads to an increase in average waiting times.

5.5 Discussion and Conclusion

5.5.1 Impact of Idle Vehicle Relocation

With shared mobility and on-demand transport services gaining steadily more ground, and the automation of vehicles pushing into the field of transport as the next 'disruptive' technology, the need for reliable simulation studies for testing operational strategies for AV and SAV is increasing. This study has shown that an important component of operating such vehicles in a large fleet is the relocation of idle vehicles during off-peak hours. In the urban context, space for idle vehicles is scarce and parking is often constrained. The relocation of idle vehicles is thus a necessary consequence of real-world parking constraints. For this reason, it is important to test for the impact of different relocation strategies when introducing SAV to a city, and specify them for example in a tendering process or when tailoring curbside management strategies. Including vehicle relocation under parking constraints to the simulation of the operation of SAV is thus an important step to increase the realism of the simulation and consequently improve the analysis of such transport services. For this reason, it is not the comparison between the *Remain* strategy and the simulated relocation per-se that is subject of analysis, but rather primarily the comparison between the different relocation strategies, which take the real-life constraints caused by the scarcity of road-space and parking-space into account. However, there are two main insights gained from referencing the scenarios with pro-active relocation strategies against a situation where parking constraints are not accounted for (i.e. *Remain*): (1) The relocation of idle vehicles does not necessarily lead to performance gains for a fleet of vehicles providing on-demand transport services. As a consequence, there is a risk of overestimating the performance of such fleets in simulations in case the relocation of empty vehicles is not accounted for. (2) Relocating idle vehicles in a pro-active manner might be outperformed by reactive relocation strategies in regard to the service efficiency and the total driven mileage. Because this finding is case-specific and depends on the spatial and temporal distribution of the demand, more research is required in order to determine the conditions under which it is favourable to apply reactive or proactive relocation strategies.

In this study, three pro-active relocation heuristics based on zonal parking availability are compared to each other, in terms of service efficiency, service externalities and service provision equity, for a case study based on the city of Amsterdam, the Netherlands. Performance differences could be detected regarding the quality of the offered service (average passenger waiting times, average trip times), the impact on traffic (local congestion, total driven mileage), the parking space usage and the spatial service provision equity (distribution of passenger waiting times).

The strategy *Demand Anticipation*, which relocates vehicles to zones with the highest number of upcoming requests, leads to short average passenger waiting times in these zones. This, however, comes at the cost of passengers experiencing longer waiting times in zones with less demand. This relocation strategy leads, overall, to the longest average passenger waiting times, and to the least equal service provision. This strategy also causes bunching of vehicles in areas close to demand hotspots, which causes local congestion and high usage of parking facilities in those areas. As a consequence for this particular case study, vehicles drive shorter distances when empty, leading to more efficient usage of the rolling stock, and cause less overall congestion in the network compared to the other two relocation strategies.

The strategy *Supply Anticipation* aims at distributing idle vehicles evenly over the zones, irrespective of the expected demand. This strategy leads, in comparison to the other two strategies, to the highest number of kilometres driven by SAV per served trip, as the SAV have longer access routes for reaching pick-up locations of passengers compared to relocation strategies taking into account future demand. This reduces the efficiency of the fleet in that regard. However, distributing idle vehicles evenly over zones leads to a more balanced usage of parking facilities.

The strategy *Demand-Supply Balancing* aims at reducing the deficit between future demand and future vehicle supply per zone, and thus combines the goals of the previous two strategies. The resulting KPI for this strategy are consequently also situated in most cases between those of the two previous relocation strategies, with the outcome of the *Demand-Supply Balancing* strategy being much closer to the one of the strategy *Supply Anticipation* than for *Demand Anticipation.* But two KPI stand out in this regard, namely the empty driven mileage, and the passenger waiting times. This strategy leads to the highest value for VKT without passengers on board, which is caused in particular by the relocation of idle vehicles. As a consequence, this strategy also leads to the highest congestion levels in the network. At the same time, this strategy also leads to the shortest average passenger waiting times and the most equal distribution of the latter.

As shown in this study, the underlying principles of a vehicle relocation strategy impact the efficiency, externalities and equity of an on-demand service. It depends on the importance one attaches to these aspects, whether one declares one of these relocation strategies to be more beneficial than the others, since the results suggest that none of them outperforms the others in all regards. When discussing the introduction of SAV to a city, main stakeholders include the (potential) users of the transport service they offer, the operator of the service, the planning authority supervising the introduction of the new service to provide a certain level of service, and the citizens (potential non-users) in the area. From the perspective of a service operator, different relocation strategies can prove to be beneficial: *Demand Anticipation* allows to reduce average waiting times in high-demand areas and to reduce driven mileage, both contributing to increased service efficiency. For this reason, most current on-demand transport services operated by drivers acting as decision-making agents are dominated by this relocation strategy. When drivers are in direct competition for passengers with each other, they create a situation closer to a stochastic user equilibrium (SUE), which does not necessarily benefit the fleet as a whole. However, once the demand, and accordingly the fleet size, reaches a level that the operation of SAV causes local congestion, it can be beneficial for an operator to cap the number of idle vehicles in high-demand areas and swap to a relocation strategy which spreads out idle vehicles more, such as the strategy *Supply Anticipation*. Increased service efficiency is also beneficial for the users of the service in terms of reducing waiting times and in-vehicles times. For passengers requesting the service in zones with low demand, a relocation strategy distributing idle vehicles more evenly is particularly beneficial, as this reduces the waiting times that they might experience otherwise. The best results in this regard could be achieved with the strategy of *Demand-Supply Balancing* for the simulated case study.

When taking the perspective of a higher planning authority, for example on a municipal level, different objectives could be leading for selecting a relocation strategy. On-demand transport shows more fluctuation over time in its performance than scheduled transport, especially regarding waiting times and reliability of indicated waiting times. There is no clear consensus yet on how to benchmark average waiting times, maximum waiting times, reliability of indicated waiting times and updated waiting times for on-demand transport services. For the simulated scenarios, the service with the overall shortest trip times (waiting time and in-vehicle time combined) is achieved with the strategy *Demand Anticipation*. This strategy also leads to the lowest value for the total driven mileage, which can be interpreted as a proxy for energy consumption and emissions of pollutants and noise caused by this transport service. However, in regard to parking consumption, the case could be made for different strategies: *Supply Anticipation* and *Demand-Supply Balancing* lead to the much more equal occupation of parking facilities in spatial terms, which can reduce pressure on the parking facilities in popular areas like city centres, and also to a higher service provision equity. Another way to look at the bunching of idle vehicles in areas of high demand caused by the strategy *Demand Anticipation* could be to interpret this as a "polluter-pays" situation: if users of other modes are not affected by the parking consumption of SAV, e.g. because these park on reserved parking spots or private ground, and the local congestion the create SAV does not affect overall network flows, this could also be an acceptable solution from the perspective of a planning authority. Which relocation principle is more favourable for a city's management of scarce parking facilities depends on the local situation, and also in regard to which potential user groups might profit most from this. As neither the strategy of *Demand Anticipation* nor the one of *Supply Anticipation* clearly outperforms the other when taking into account the holistic set of KPI presented in this paper, a compromising strategy like the *Demand-Supply Balancing* strategy has the potential to provide the necessary attenuation of undesired effects.

5.5.2 Study Limitations and Outlook

The analysis of the relocation heuristics is based on the simulation of a case study. This set-up does not allow to draw universal conclusions, and should be generalized or transferred to other contexts with caution. The main limitations of this study are linked to two input parameters: (1) the zonal division and (2) the behavioural model used to describe the users' response in the agent-based model.

(1) The zonal division is expected to have an important impact on the working of vehicle relocation strategies based on demand and vehicle supply aggregated on a zonal level. For this study, the zones have been based on postal code areas which are commonly used in the Netherlands for defining parking regulations. However, depending on the goal of a relocation strategy, other criteria for the zonal divisions could be selected, e.g. a zonal division based on the current quality of scheduled public transport services. More research is required to determine the optimal (or good enough) number of zones, their size, and their defining principles in order to come to satisfying conclusions on zonal relocation strategies under parking constraints.

(2) In regard to the behavioural model used, the current state of research on mode choice behaviour in an era of SAV is not developed enough in order to confidently apply choice models to simulation models. In this paper, basic assumptions have been made about the specifications of the SAV service and on the perception of the different elements linked to a trip taken in an SAV. As for now, any simulation study featuring

SAV can only be interpreted in light of the assumptions made for the underlying behavioural model.

Further limitations of this study are caused by other simplifications made for the simulation of the case study, such as that parking spots are dedicated for SAV and can be reserved upfront by the operator. Future research into the distribution of parking spots for SAV and the allocation of free parking spots will be an important aspect in the development of dynamic fleet operation paradigms. This is particularly important if more than one fleet of SAV compete with each other for parking space, or if they compete with individual drivers of (non-)automated vehicles. Furthermore, the performance of the different relocation strategies for idle vehicles should also be tested for other operational scenarios, most importantly for SAV operated as a pooled service. The operational differences for pooled services mainly impact the vehicle routing problem and vehicle dispatching problem, however, also the performance of vehicle relation strategies can change due to pooling. When operating SAV as a simultaneously shared service, instead of a sequentially shared one, vehicles likely turn idle less often, and they turn idle at different locations in the network. Which relocation strategy performs best in such a setting highly depends on local conditions and should be carefully tested for the different performance indicators presented in this study.

The analysis in this study is based on one specific case study in order to retrace the impact of three simple vehicle relocation heuristics. Based on this set-up, future work will investigate further the interplay between the fleet size of SAV and the number of reserved parking facilities, and curbside management strategies will be concretized in order to test the impact of parking policies for SAV.

Part III – Parking Management

The process of policymaking in the field of transportation is often a reactive one, with policies following changes in travel behaviour, technology advancements and the appearance of new mobility services. The presence of unprecedented modes is especially likely to challenge policymakers to overhaul old policy principles if new classifications are required, which also involves defining rules, rights and regulations for such modes: for example, should people on roller skates be allowed to use the sidewalk or the cycle lane, and what about electrified skateboards and e-scooters? Are car-sharing vehicles public transport vehicles, and if so, should they be allowed to use bus lanes and be granted access to special parking spaces? Such questions can often only be answered after some experience with the new modes has been gained, and policies for new modes emerge accordingly in the course of time, once related issues and opportunities become apparent.

Polices for automated vehicles are expected to take shape in an equally adaptive process, following the opportunities and issues created by the introduction of such vehicles. Therefore, it could happen that in the early days of shared automated vehicles no all-comprising legal framework and according policies will be in place. This, however, does not mean that the introduction of shared automated vehicles cannot be shaped and influenced by transport authorities from the very beginning. In this part (Chapter 5), parking management strategies are applied to shared automated vehicles to improve the service efficiency and equity, while reducing undesired negative externalities. Parking management is something that policymakers are very familiar with, that does not require changes in the legal framework and that can be applied to a broad range of modes, making it flexible enough to accommodate changing technology and transport services.

Chapter 6 - Parking Space for Shared Automated Vehicles: Why Less Can Be More

This chapter is based on: Winter, K., Cats, O., Martens, K., van Arem, B. Parking Space for Shared Automated Vehicles: Why Less Can Be More. Under Review.

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 sequentially 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. 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.

6.1 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.

Autonomous vehicles (AV) promise to bring various benefits, ranging from improved traffic safety for all road users (Fagnant & Kockelman, 2015; Greenwald & Kornhauser, 2019; Sperling et al., 2018), improved traffic flows and reduced mobility costs (Dong et al., 2017; Greenwald & Kornhauser, 2019), 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 (Greenwald & Kornhauser, 2019; Harper et al., 2018) 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 & Kornhauser, 2019; Spurling, 2020).

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 & Kornhauser, 2019). The fact that such vehicles are self-driving offers three game-changers: (1) The costs for on-demand transport would 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 & 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 & Alemi, 2018; Jiang, Chen, Mislove, & Wilson, 2018; Winter, Cats, Marten, & van Arem, 2019), increasing the total driven mileage due to relocating or idle cruising of the vehicles (Circella & Alemi, 2018; Winter et al., 2019) and providing lower-quality or higher-cost services to passengers located at locations that require long access or egress times for SAV vehicles (L. Chen, Mislove, & Wilson, 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. While in the long-term, SAV-parking may be regulated through legal agreements as part of public tenders, this is unlikely to be the case in the early stages of SAV introduction. In this early stage, local authorities are likely to allow several SAV operators to freely enter the market, each using its 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.

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 & Kornhauser, 2019; Winter et al., 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., 2019)), 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; Winter et al., 2019; W. Zhang et al., 2015).

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. The analysis of these scenarios is performed mainly from the perspective of a transport authority, but also discusses the implications for other stakeholders. 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.

The remainder of this paper is structured in the following way: In section 6.2, a review of the current literature sketches what parking management strategies for SAV have been envisioned. In section 6.3, 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 6.4, and discussed in the concluding section.

6.2 Parking Self-Driving Vehicles and On-Demand Transport Vehicles

Autonomous vehicles are still in a testing phase, and larger fleets of centrally dispatched shared autonomous vehicles are not yet operational. In the following, we review findings from studies that modelled parking management strategies for SAV, as well as findings on parking use and parking management of ride-hailing services and taxis.

6.2.1 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 & 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 (Mingardo et al., 2015; Simićević, Vukanović, & Milosavljević, 2013) (3) users' restriction, e.g. parking for residents only (Kaspi, Raviv, & Tzur, 2014; Mingardo et al., 2015; Molenda & Sieg, 2013) and (4) pricing parking by the introduction of fees (D'Acierno, Gallo, & Montella, 2006; Migliore, Burgio, & Di Giovanna, 2014; Mingardo et al., 2015; J. van Ommeren & Russo, 2014). 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 & 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 & Dowling, 2016; Zvolska, Lehner, Voytenko Palgan, Mont, & Plepys, 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).

6.2.2 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 and current parking pricing policies, privately-owned AV can be expected to mainly park just outside the city centre or other demand-hotspots (Fagnant & Kockelman, 2015; Zakharenko, 2016). 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., 2019). 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.

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, Bahrami, & Roorda, 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 in off-peak hours a substantial part of the fleet will be idle, and these vehicles have to park somewhere.

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., 2019). Transport authorities could enforce such a relocation strategy only by having legal agreements with the operator (e.g. through a tender or concession). However, we foresee that especially in the introductory phase of SAV, such opportunities of influence will be limited, not least because of a lack of experience with tendering large-scale on-demand SAV-based public transport services. Instead, formulating parking restrictions for SAV is arguably a more feasible approach for transport authorities, amongst others because it will apply to all SAV operators entering the market. For this reason is the focus of this study expanded 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.

6.3 Application

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 Chapter 5. For this case study, we specify a set of parking management scenarios in section 6.3.1 which we then analyse for three main stakeholders, whose role we discuss in section 6.3.2. The input used in our simulation study, in particular regarding the demand for SAV and the fleet specification, is described in section 6.3.3 and 6.3.4.

6.3.1 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. 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 Figure 6.1. The exact location of the parking spots and depots in the network (see Figure 6.2) is shown in Figure 6.3a-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 Figure 6.3a-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 Figure 6.2) is based on the parking zones defined by the municipality of Amsterdam as of April 2019 (Gemeente Amsterdam, 2018). In scenario *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 6 p.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 city centre of 5 minutes and 60 minutes, respectively, is introduced.

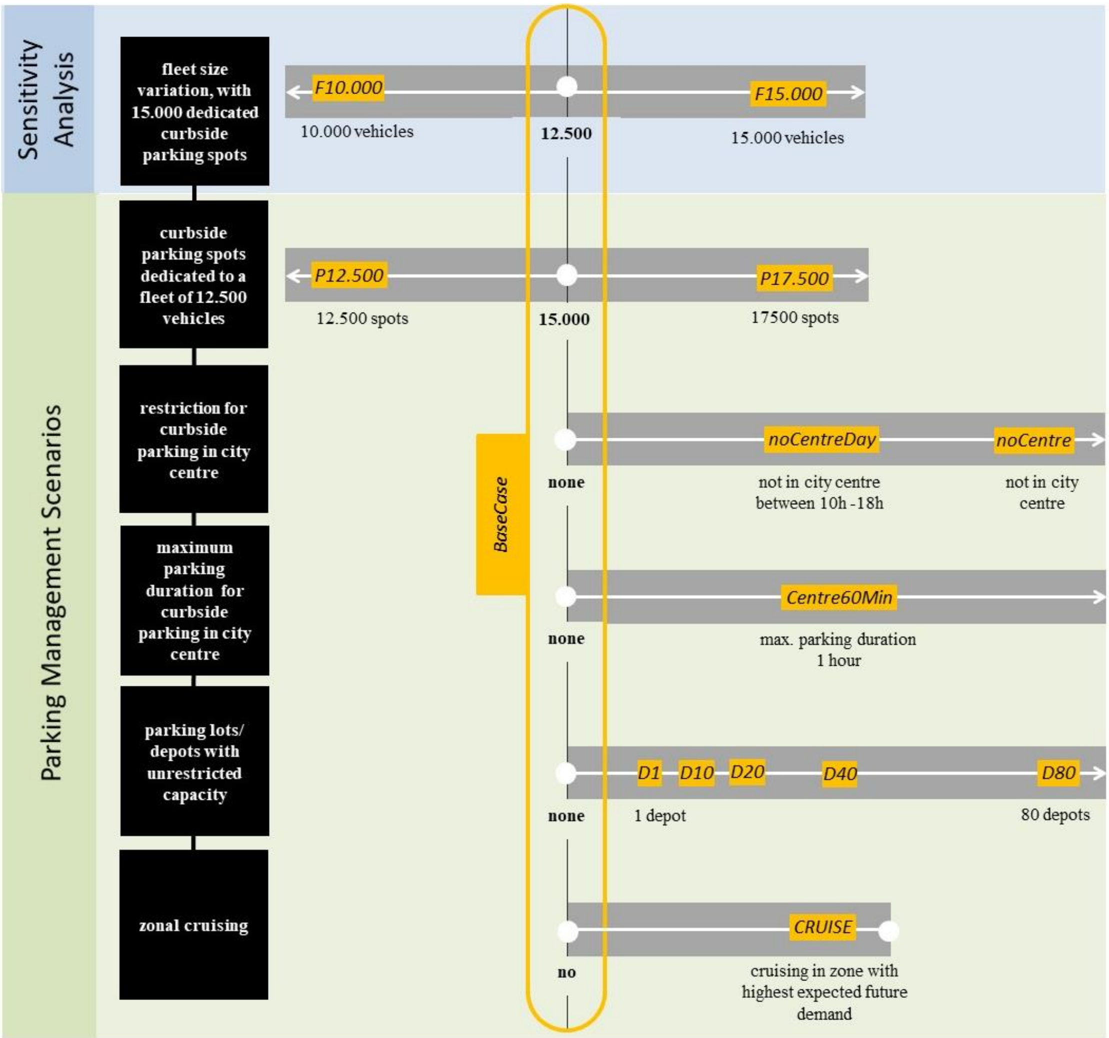


Figure 6.1: Scenarios for which the on-demand transport service operated with SAV is simulated in this study

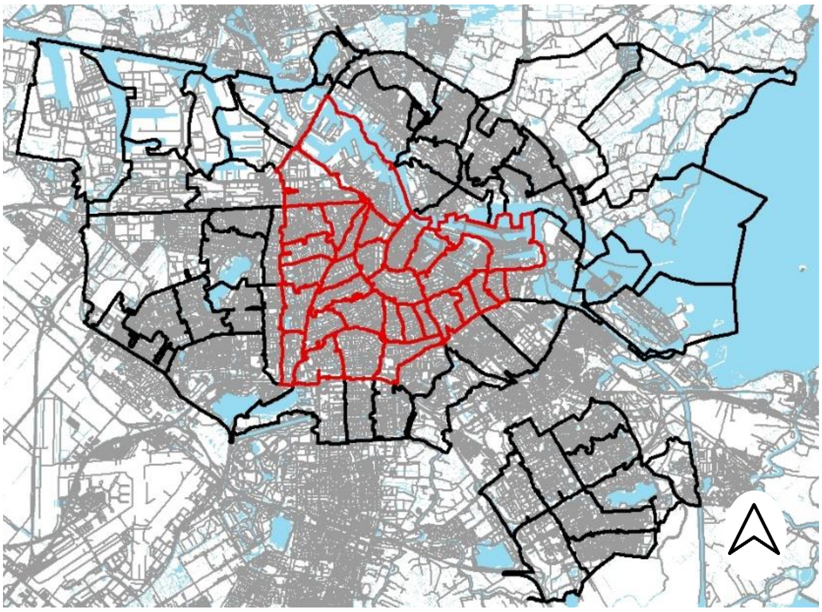


Figure 6.2: City boundaries and zonal division of the city of Amsterdam based on postal codes. Zones covering the inner city of Amsterdam are outlined in red

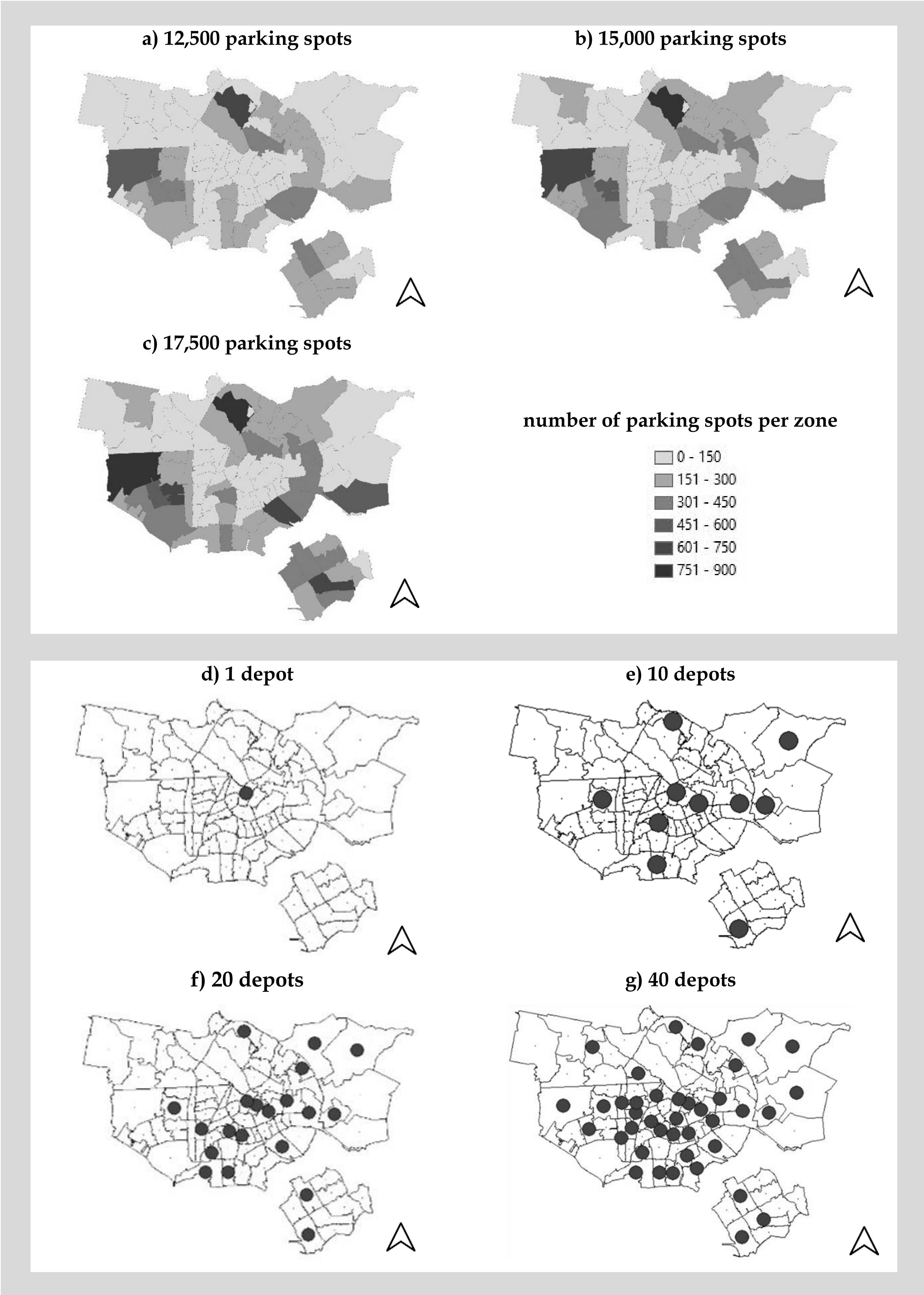


Figure 6.3: Illustration of the spatial distribution of the simulation input: a)-c) showing the number of parking spots per zone for scenario P12,500, BaseCase and P17,500; d)-g) showing the location of parking depots for scenario D1, D10, D20 and D40

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 Figure 6.3e -g.

6.3.2 Stakeholders

The effect of the parking management strategies is analysed in this paper for three main stakeholders: the "transport authority", the "fleet manager", and the "customers". The on-demand transport service provided by a fleet of SAV is envisioned in this study as an addition to a city's public transport services and in parallel to continued use of regular (or automated) private vehicles. The role of these three stakeholders is described in more detail in the following:

(1) The "transport authority" is the organisation providing the infrastructure used by the fleet of SAV, such as roads, drop-off zones and parking facilities. The "transport authority" desires a transport service that provides the best service possible to the "customers" while reducing undesired external effects such as air pollution, greenhouse gas emissions, congestion or clogging areas with parking or cruising vehicles. The transport authority also has an interest in limiting the space required to provide dedicated parking spots for SAV. The on-demand transport service is envisioned as a public (transport) service, requiring that all citizens have access to the service and service fees are universal and depend only on the distance travelled in the SAV. This means that no request should get declined, nor that monetary compensations are made for efficiency reasons, e.g. off-peak fares or different fares for different regions within the service area. The quality of the transport service is defined by the average passenger waiting time, but the transport authority has also an interest in minimizing the disparities in waiting times to increase the service provision equity. In our scenarios, it is also the "transport authority" who decides where, when and for how long idle SAV are allowed to park within the city boundaries by specifying where the dedicated parking spots for SAV are located, and by specifying the rules that apply to their usage by SAV.

(2) In this study, there is only one "fleet manager" providing the envisioned transport service operated by SAV. The "fleet manager" has full control over the individual vehicles of the fleet and can decide on the dispatching and relocation process, as long as any potential service provision objectives such as a maximum for average passenger waiting times set by the "transport authority" are met and none of the parking restrictions are violated. The "fleet manager" aims at managing the fleet as efficiently as possible in regard to vehicle utilisation while reducing the average vehicle mileage in order to increase the profit. In our scenarios, it is the "fleet manager" who decides where idle vehicles park on the dedicated parking facilities.

(3) The “customer” chooses to travel with the on-demand transport service based on a mode choice model specified in Chapter 5, which is based on the concept of utility maximisation. In the simulation of users’ choices in this study, the two main elements influencing the utility of travelling by SAV are (a) the passenger waiting time and (b) the travel time in the vehicle.

6.3.3 Demand

The case study, for which the different parking management scenarios are tested, is based on the city of Amsterdam in the Netherlands (see Figure 6.2). This testbed for parking management strategies is similar to the one described in Chapter 5. We simulate 129,485 trips performed in SAV per day (represented by 20% in the simulation), resulting in a modal share of 4.3% for SAV. The average distance travelled per simulated trip by SAV is 12 kilometres. The spatial and temporal distributions of the passenger requests are shown in Figure 6.4. The demand is kept inelastic for testing the impact of the different parking management strategies on the key-performance indicators described in section 6.4.

a) Passenger Requests per Zone ***b) Passenger Requests per Hour***

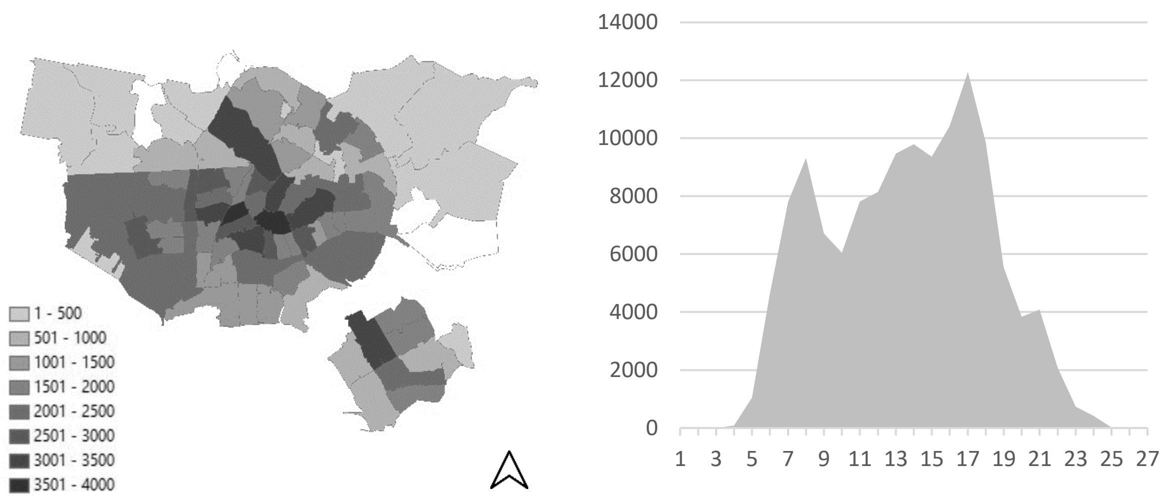


Figure 6.4: a) daily passenger requests per zone, b) daily passenger requests per hour

6.3.4 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). A detailed description of the simulation process and the applied parameters is provided in Chapter 5. 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).

The performance of the parking management strategies formulated by the “transport authority” is tested for a demand-anticipatory relocation strategy formulated by the “fleet manager”, 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. The impact of parking management strategies 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 highlights best the working of parking management, as well as its limits.

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. Based on this, the three zones with the highest demand with currently free parking facilities in this 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 Chapter 5. 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 minutes.[5]

6.4 Results

6.4.1 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 15,00 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 6.1a). The results for the average passenger waiting times and empty VKT for each scenario are summarized in Table 6.1b and 1c and are visualized in relation to the ratio of vehicles per dedicated parking spots in Figure 6.5.

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 17,500,

[5] For the results for a scenario in which vehicles cruise randomly through the network, please the Appendix.

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 Figure 6.5, 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 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 providing more vehicles.

Table 6.1: 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.

a) Ratio Vehicles/Dedicated Parking spots

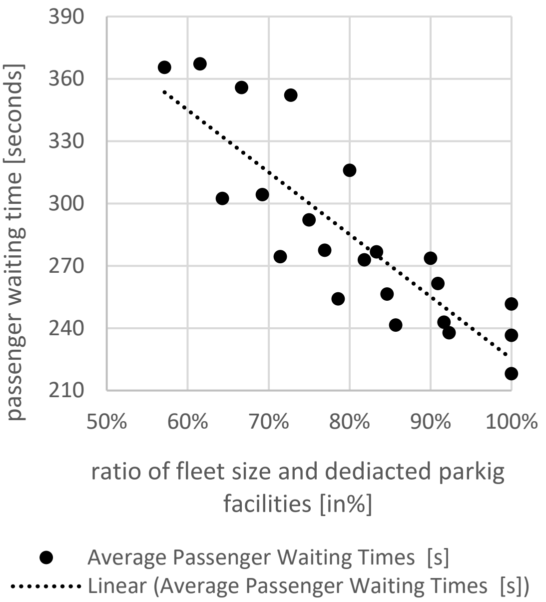
fleet \ parking	12,500	13,750	15,000	16,250	17,500
10,000	0.80	0.73	0.67	0.62	0.57
11,250	0.90	0.82	0.75	0.69	0.64
12,500	1.00	0.91	0.83	0.77	0.71
13,750		1.00	0.92	0.85	0.79
15,000			1.00	0.92	0.86

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



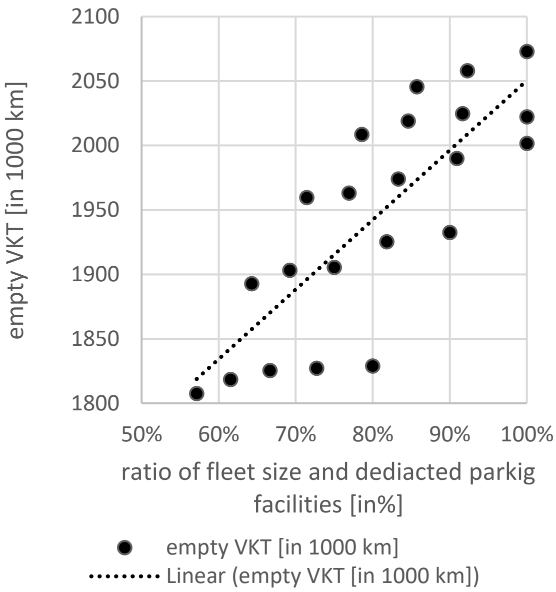


Figure 6.5: Service performance in respect to the ratio between fleet size and parking facilities, expressed in average passenger waiting times (left) and empty vehicle-kilometres-travelled (right)

6.4.2 Impact of Parking Management

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 minutes 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 of the "transport authority": 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.

Service Efficiency

In this section we address the impact of the different parking management scenarios on service efficiency with regard to two major KPIs (see also Table 6.2): the empty vehicle mileage and the passenger waiting time. In order to gain more understanding of the role of the spatial dispersion of idle vehicles plays in regard to service efficiency, we conclude this section with a comparison of these KPIs for the scenarios featuring depots.

Empty Vehicle Mileage

Operating the fleet as efficiently as possible is a prime goal of the "fleet manager". 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 6.2). 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 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.

Table 6.2: Key-Performance-Indicators describing the service efficiency 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 60min***	***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

Passenger Waiting Times and Trip Times

The passenger waiting time is the leading KPI for “customers”. As can be seen in Table 6.2, is the average passenger waiting time for scenario *P10,000* 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).*

It is not just the waiting time that determines the efficiency of the service, but also the time needed to complete a full trip. The time for a trip in a SAV experienced by a passenger is in our case a combination of waiting time and the in-vehicle time (IVT), as for reasons of simplification the time it takes to board and exit a vehicle is constant. The waiting times have a strong influence on this indicator, as the differences between the different scenarios are less pronounced for IVT than for waiting times (see Table 6.2). Consequentially, the worst performance for this KPI is reached for the scenario *NoCentre* and the scenario *D80,* and the best for the scenario *P12,500* and *P17,500*. More details of the IVT as a result of congestion in the network are discussed in the following section.

The Role of Vehicle Dispersion

To gain a better understating 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 Figure 6.6, it can clearly be seen how average passenger waiting times decrease with an increase in the number of depots dropping from 20 minutes for *D5* to less than 7 minutes 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 Figure 6.6 it also becomes apparent that adding more depots does not necessarily improve the efficiency of the SAV transport service, once a good level of service has been reached: the average passenger waiting time improves by 31 seconds from scenario *D40* to *D80* (decrease by 7.8%), while the average driving speed reduces by 2.4 % from 42.3 km/h to 41.3 km/h. This strengths the observation that neither bunching at strategic locations by design (such as in scenario *D1 at the city centre),* nor bunching around demand-hotspots (such as in scenario *D80*) are favourable for the efficiency of the service.

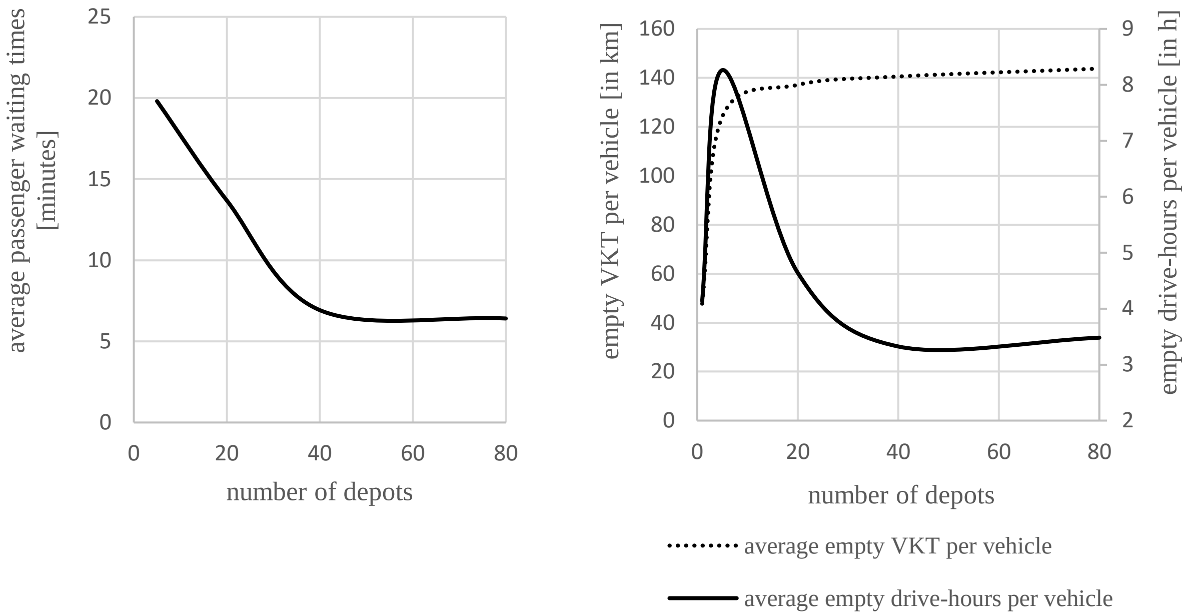


Figure 6.6: Average passenger waiting times (left) and average empty VKT and empty vehicle-drive hour per vehicle (right) as a function of the number of depots (scenarios ranging from D5 to D80)

Service Externalities

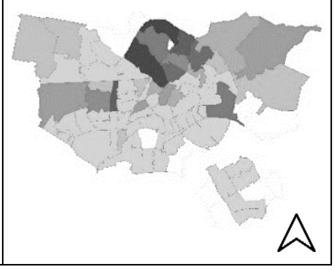
The externalities of the service are discussed on the basis of three leading KPIs (Table 6.3): (a) the average driving speed of the SAV as a proxy for congestion in the network, (b) the total VKT as a proxy for energy consumption and harmful emissions such as particular matter, greenhouse gases or noise, and (c) the distribution of parking space consumption as a proxy of local disturbances caused by bunching idle vehicles.

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 6.2. 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 minutes, for the scenario *P12,500* this is 18.3 minutes and for *P17,500* is

17.9 minutes. This leads to an increase in IVT for the total of all SAV users per day of 442 hours for *P12,500* and a reduction of 474 for scenario *P17,500* compared to the *BaseCase*.

Table 6.3: Key-Performance-Indicators describing the service externalities for selected parking management scenarios

<table>
<tr><th></th><th colspan="6">parking management strategies with parking space constraints</th><th colspan="2">free of parking constraints</th></tr>
<tr><th></th><th>P12,500</th><th>Base Case</th><th>P17,500</th><th>No Centre</th><th>No Centre Day</th><th>Centre 60min</th><th>D80</th><th>Cruise</th></tr>
<tr><td>Average driving speed taxis [in km/h]</td><td>38.7</td><td>39.2</td><td>40.0</td><td>40.6</td><td>40.6</td><td>41.3</td><td>41.2</td><td>37.6</td></tr>
<tr><td>Total VKT [in 1000 km]</td><td>3,550</td><td>3,520</td><td>3,505</td><td>3,585</td><td>3,570</td><td>3,580</td><td>3,340</td><td>11,930</td></tr>
<tr><td>Gini-index zonal parking usage 9pm- 10pm</td><td>0.26</td><td>0.36</td><td>0.42</td><td>0.53</td><td>0.53</td><td>0.52</td><td>0.74</td><td>--</td></tr>
<tr><td>Usage of zonal parking usage between 9 and 10 p.m. [in %]</td><td colspan="3">P12,500</td><td colspan="2">Base Case</td><td colspan="3">D80</td></tr>
<tr><td>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%</td><td colspan="3"></td><td colspan="2"></td><td colspan="3"></td></tr>
</table>

Energy Consumption and Emissions
In the following, we do not make any assumption on the propulsion engine, filter technology, tyres or other vehicle components potentially used for SAV. We focus instead on the VKT as a proxy KPI in this regard.

Overall, it can be observed that the gains in driving speeds of SAV achieved by relocating idle vehicles to locations outside of city centres, as discusses in the previous section, are counteracted by the increase in VKT: the closer vehicles can park to future demand locations, the shorter are the distances travelled without passengers on-board and consequently, the lower is the total of VKT in case of inelastic demand. 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.

Parking Space Consumption
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. 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 the differences in the Gini-index being more extreme after the evening peak compared to the morning 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 9 p.m.

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 (Figure 6.7). 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 6.3, 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.

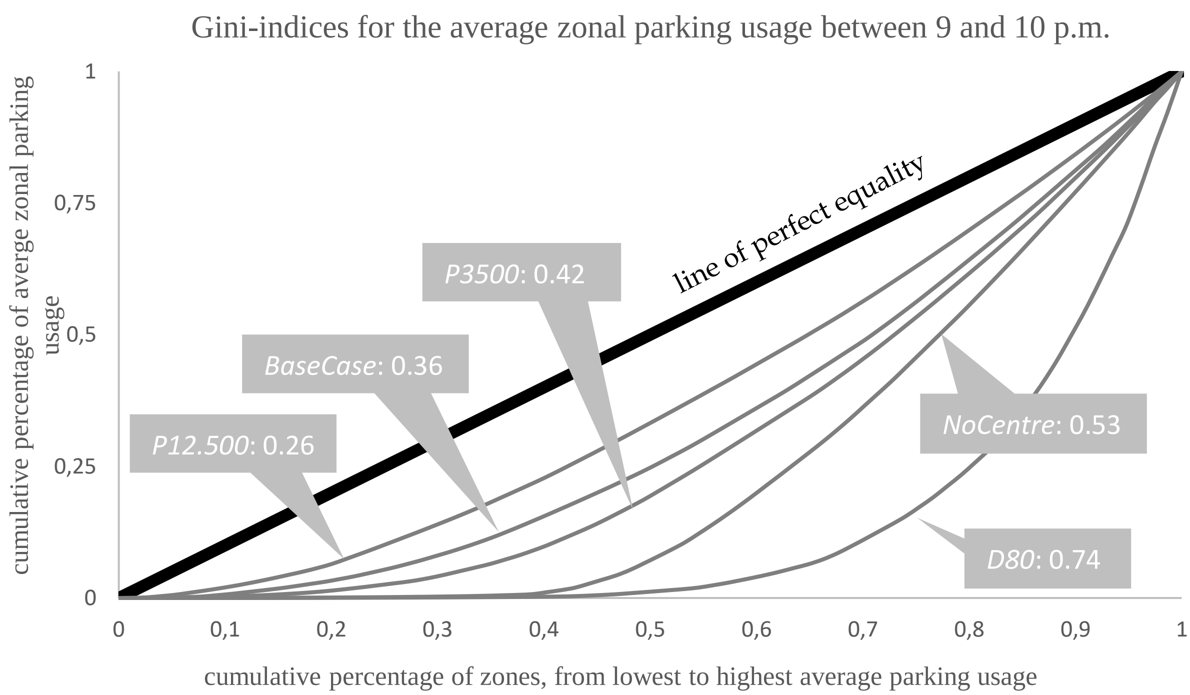


Figure 6.7: Lorenz curves for the average zonal parking usages for the scenarios P12,500, BaseCase, P17,500, NoCentre and D80.

Service Provision Equity

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 distinction is made between groups of different user characteristic. The impact of spreading out idle vehicles on the average passenger waiting times has already been discussed in section 4.2.1, with the main observation being that the more idle vehicles are spread out through the network, the lower the average passenger waiting times.

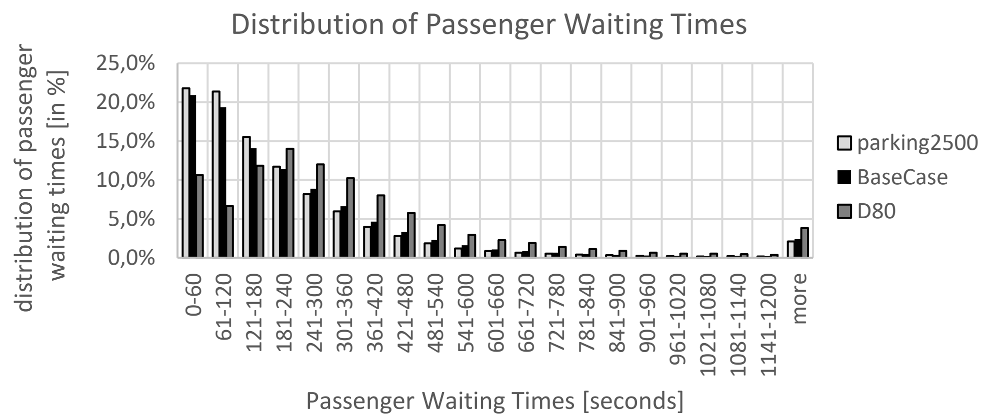
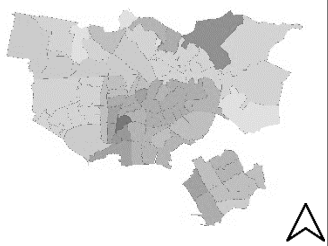
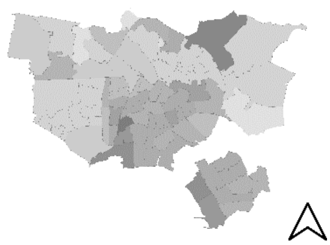
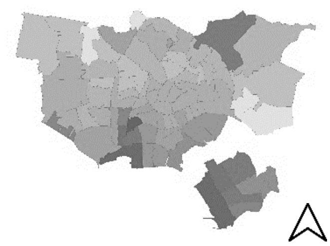
Distribution of Passenger Waiting Times

Spreading out idle vehicles reduces not only the average passenger waiting times, but also the distribution of the passenger waiting times becomes more equal. As can be seen in Table 6.4, where the distributions for the passenger waiting times are shown exemplarily 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 minutes, 34% having waiting times between 2 and 5 minutes, and about 25% of all passengers having waiting times longer than 5 minutes, including 3% experiencing waiting times longer than 15 minutes. For the scenario *P80* however, the distribution shows a clear hump: only around 17% of the passengers are served instantly (maximum 2 minutes of waiting time), and the peak of the distribution occurs between 2 and 5 minutes of waiting times (around 38%), with a peak at around 3 to 4 minutes of waiting time. The tail of the 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 minutes 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 minutes) than when spreading idle vehicles out in the network. Spreading out vehicles also counters very long waiting times (longer than 15 minutes) more efficiently.

Spatial Distribution of Passenger Waiting Times

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 6.4 that spreading out vehicles as much as possible not only reduces the average passenger waiting times, but also leads to a lesser geographical dispersion 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 Figure 6.8, 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 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.*

Table 6.4: Key-Performance-Indicators describing the service provision equity for selected parking management scenarios

<table>
<tr><th></th><th colspan="6">parking management strategies with parking space constraints</th><th colspan="2">free of parking constraints</th></tr>
<tr><th></th><th>P12,500</th><th>Base Case</th><th>P17,500</th><th>No Centre</th><th>No Centre Day</th><th>Centre 60min</th><th>D80</th><th>Cruise</th></tr>
<tr><td>Gini-coefficient for average zonal passenger waiting times</td><td>0.28</td><td>0.29</td><td>0.28</td><td>0.34</td><td>0.33</td><td>0.34</td><td>0.21</td><td>0.25</td></tr>
<tr><td>Distribution of Passenger waiting times [in seconds]</td><td colspan="8">
</td></tr>
<tr><td>Average passenger waiting time per zone (in seconds)</td><td colspan="3">P12,500</td><td colspan="3">Base Case</td><td colspan="2">D80</td></tr>
<tr><td>
</td><td colspan="3"></td><td colspan="3"></td><td colspan="2"></td></tr>
</table>

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.

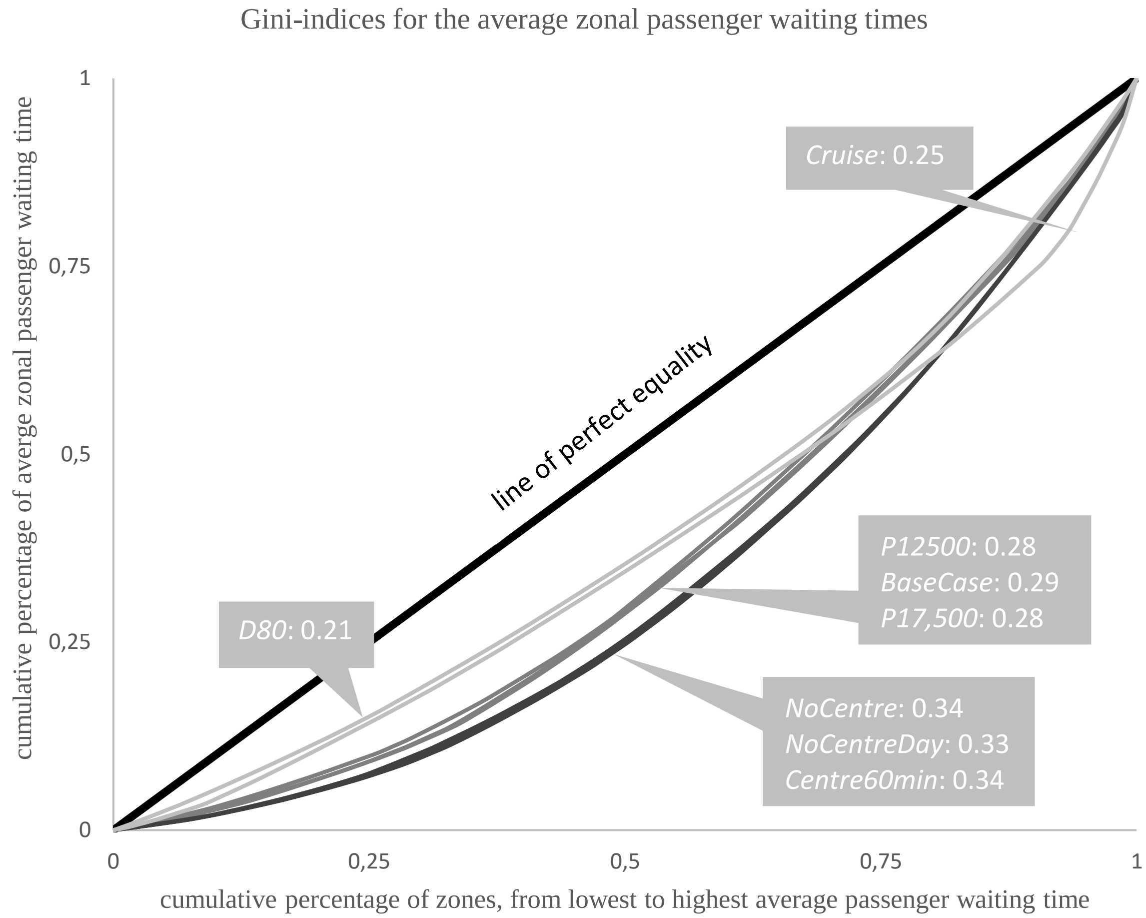


Figure 6.8: Lorenz curves for the average zonal waiting times for the scenarios P12,500, BaseCase, P17,500 (all medium gray), NoCenter, NoCentreDay, Centre60min (all dark grey), D80 and Cruise (both light grey).

6.5 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 achieving 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.

6.5.1 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 superimposing policies at the local level if necessary, e.g. as done in this study by limiting parking in the inner city. Similar effects could alternatively be achieved by amending the relocation algorithm of the fleet manager, as done in Chapter 5. 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 into relocation algorithms, which 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 6.5 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 Chapter 5, 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 can reduce passenger waiting times less efficiently than the internal parking restrictions formulated by the relocation strategy. Again, this gain comes at the cost of additional empty mileage driven by the SAV. This comparison shows that internal, or "virtual" parking constraints specified by relocation strategies for SAV can have a greater impact than the parking management strategies per-se. 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 rather than in terms of physical parking constraints by a “transport authority”.

Table 6.5: 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

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, as this does neither require insight into the relocation strategy applied by the fleet manager nor does it require direct coordination between multiple fleet operators.

6.5.2 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 of 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 of 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.

Chapter 7 - Conclusion

Worldwide, pilot studies and trials with fully autonomous vehicles are conducted, heralding a future in which self-driving vehicles might play an important role for our mobility. Self-driving vehicles (level 4 and 5 in the SAE classification) have the potential to be a true disrupter in the field of transport, as they might change the way we travel and challenge both the current market for private vehicles as well as the current public transport system. By being able to move without a human driver on board, they make modern car-sharing concepts as well as on-demand transport services more feasible. Shared automated vehicles (SAV) are therefore often sketched as one of the first applications of self-driving technology. This thesis combines the findings from three main research branches addressing the possible impacts of shared automated vehicles: behavioural research describing the preferences of potential users of such vehicles (Part I), operational research improving the way such vehicles are put into use (Part II) and research into policy implications for such vehicles (Part III).

7.1 Main Scientific Findings and Their Practical Implications

7.1.1 Preferences for Self-Driving Vehicles Used for Public Transport Services

The first of the three main research questions addressed in this thesis asks, who the users of self-driving vehicles deployed in road-bound public transport services (automated buses or SAV) might be and what influences the choices for or against using such services. In order to analyse the preferences towards self-driving vehicles used for public transport services, two stated-preference experiments have been conducted, based on which discrete-choice models have been estimated. The findings from these experimental studies contribute to the growing body of work analysing preferences towards, as well as perceptions of, self-driving vehicles in general and shared automated transport services in particular.

The results of the stated-preference studies suggest that operating public transport services with automated vehicles does not improve the preference for such services for all people alike.

Participants with the strongest preferences towards self-driving vehicles used for public transport services have been found to be more likely young, male, with higher education and participants who are more sensitive towards travel-time reduction rather than travel-cost reductions. In terms of the current commuting behaviour, it has been observed that multi-modal users currently combining private car and public transport services show the highest preference for shared automated vehicles.

The characteristics of those with higher preferences for self-driving vehicles deployed for public transport services, and the flexibility in service they enable, fit at large the picture we generally have of early adopters of new technologies. Generally speaking, this group is however neither the largest group among public transport users nor is it the group most dependent on public transport services. This leads to the conclusion that the introduction of self-driving vehicles for public transport services would initially be met with some scepticism by most of the current users of public transport services, but would have the potential to directly meet the travel demands of a highly mobile group of people currently combining public transport services and the usage of their private cars as part of their commuting trips.

It also has been found that on-demand transport services are not preferred over scheduled services by public transport users per se. A shift in preference towards such flexible transport services would require these services to provide a clear benefit over existing forms of public transport, either by being noticeably cheaper or faster. Commuters currently using exclusively their private car have been found to show an increased preference towards vehicle sharing in the form of free-floating car-sharing, but not towards self-driving vehicles. Their preference for free-floating car-sharing services increases further if parking fees for private cars are applicable or if the search for a parking spot costs more time when using a private car than when using the car-sharing vehicle. This shows a potential route for policies aiming at stimulating the use of car-sharing vehicles instead of private cars.

7.1.2 Benefits of Idle Vehicle Relocation for Shared Automated Vehicles

The operation of fleets of vehicles providing on-demand transport services has moved into the focus with the rising popularity of ride-hailing services and the development of self-driving vehicles progressing rapidly. In the scientific world, especially the request-dispatching and routing of shared vehicles attracts attention. The relocation of idle vehicles is often treated as a subordinate step of these operational tasks. For this reason, the second main research questions addressed in this thesis asks, what role the relocation of idle vehicles can play in the operation of SAV. The findings presented in this thesis suggest that idle vehicle relocation can be not only a crucial component for efficient and effective service operation, but can also be used to achieve other objectives such as service provision equity or reduced service externalities. The relocation strategies tested for the on-demand transport services described in this thesis do not take into account the individual objectives of vehicles (or drivers), and hence are more suitable to fleets of automated vehicles than fleets of manually driven vehicles.

The tested relocation strategies include idle cruising, placing idle vehicles in zones with high demand, spreading idle vehicles out as much as possible and a combination of the two latter strategies. None of the tested relocation strategies was found superior in all respects, but for the different simulated testbeds the strategy of spreading out idle vehicles throughout the network has shown benefits from an operator’s point-of-view: it avoids creating congestion around demand-hotspots, which overall leads to shorter average passenger waiting times. However, spreading out idle vehicles comes at the cost of higher total vehicle-kilometres travelled, which can reduce the efficiency of the operation.

Which of the relocation strategies is the most advantageous one depends on the market in which the transport service offered by the SAV is operating. Demand-anticipatory relocation strategies could be preferred by operators in a highly competitive market, in which several fleets vie with each other for customers. In such a setting, fleet managers could find it beneficial to strategically position idle vehicles so that they have a higher probability of reaching a large number of customers faster than their competitors. If, however, the on-demand transport service would be operated in a less competitive environment, a relocation strategy aiming at spreading out idle vehicles could prove to be a better operational choice, considering its benefits in terms of service efficiency and service provision equity, as found in this thesis.

7.1.3 Proactive and Reactive Vehicle Relocation of Shared Automated Vehicles

The results presented in chapters 4 to 6 of this thesis open up the question whether proactive vehicle relocation strategies for idle SAV are advantageous compared to reactive relocation strategies, which neither take future demand nor future supply distribution into account. In this thesis, various proactive and reactive strategies have been tested, with the results of the reactive strategies presented in concise form in the Appendix. The following main conclusions can be drawn from this comparison between proactive and reactive relocation strategies for idle SAV:

- **Not moving idle vehicles can outperform proactive relocation strategies:** The scenario *Remain With Parking Constraints* is the most passive relocation strategy simulated with parking constraints. This strategy leads to considerable gains in the service efficiency, as vehicles move shorter distances for reaching their next parking location, which leads to less empty VKT, hence also to less congestion and ultimately to shorter trip times. The passenger waiting times are equally low as for the *Demand Supply Balancing* strategy, but slightly less equally distributed than for this proactive strategy, as can be seen by comparing the 95% percentile of passenger waiting time and the Gini-index of zonal waiting times. This shows that by staying close to the destination of passenger trips, the chance of meeting future demand increases similarly than when spreading vehicles out according to the most advanced relocation heuristic tested in this thesis.
- **Unregulated cruising should be avoided:** The results obtained for the scenario *Cruise* and *Random Cruise* show that zonal cruising and random cruising through the network cause severe congestion (driving speeds are much lower than in the other cases), which negatively affects all service efficiency parameters. This is true for both reactive and proactive cruising strategies. The latter, however, causes fewer disruptions in the network. This leads to the conclusion that if cruising cannot be avoided, it should be at least be stirred to a more proactive pattern in order to reduce the randomness of the cruising.
- **Not simulating parking constraints leads to an overestimation of the service performance of SAV:** The strategy *Remain* describes a hypothetical case in which idle vehicles remain at the latest drop-off location regardless of the availability of parking space at this location. In the simulated case study, this leads to an overestimation of the service performance of SAV, as this “strategy” outperforms all other ones. The reason for this is two-fold: (1) By positioning vehicles at the destination of passenger-trips, the likelihood increases to be positioned close to future demand, and (2) systematic delays caused by the discontinuous updating of the simulation increase passenger waiting

times, which is the case for all other relocation strategies where the additional “actions” (start relocation, end relocation and turn to parking) cause laggardness. The latter issue could, however, be overcome by continuously improving the technical specifications of the simulation of SAVs.
The comparison between the scenarios *Remain* and *Remain With Parking Constraints* shows that the consideration of parking constraints leads to an increase in the average passenger waiting times by 46% and of the total VKT by 40%. The VKT are not subject to systematic distortions caused by the discontinuous simulation approach, and hence show the degree to which the performance of SAV can be overestimated when not taking into account parking space constraints for the simulated case study.

The comparison between proactive and reactive relocation strategies thus leads to two key observations: (1) Parking constraints are an important factor to be considered when simulating on-demand transport services such as the one envisioned here to be operated by SAV and should be carefully included when judging the performance of such services. (2) Proactive relocation heuristics do not necessarily outperform reactive relocation strategies. This is, however, a case-specific finding for the simulated case study with its distinctive demand pattern, zonal division and parking supply. Different demand patterns (spatially or temporally) and different parking supply per zone could lead to another outcome in this regard, which emphasizes how important it is to repeat similar simulation scenarios and relocation strategies for a large variance of case studies and service specifications before coming to conclusive judgments of how SAV could, and perhaps should, be operated.

7.1.4 Parking Management for Shared Automated Vehicles

The final main research question addressed in this thesis asks, how parking management can effectively shape the way SAV perform in our cities. As shown in the analysis of the different strategies for relocating shared automated vehicles, idle vehicle relocation impacts not just the operational performance of the service, but also externalities caused by such a transport service as well as its service provision equity. This opens up an alley for transport authorities to take an active role in shaping the impact of SAV by defining where, and for how long, idle vehicles may park.

In this thesis, parking management is shown to be an effective way to manage service externalities and service provision equity of on-demand transport services operated by SAV, while preserving adequate levels of operational efficiency. This can be particularly useful in cases where no agreement on vehicle relocation with the operator can be obtained, e.g. due to a lack of a legal framework or because multiple competing services are operated in the same area. Depending on the objective of the transport authority, issues such as service provision equity, spatial usage, congestion or the environmental impact of such transport services can be addressed by defining respective parking management strategies. The results of this study have shown that transport authorities do not have to provide an abundance of dedicated parking space in order for such transport services to be able to operate efficiently. The results in this thesis show that providing more parking space than necessary can even decrease the service efficiency in a situation where fleet managers relocate their vehicles based on demand-anticipatory strategies. When looking at the average passenger waiting time, it has been shown that the improvement attained through parking management is much higher than by increasing the fleet size. This can reduce the operational costs as well as the total parking space needed for such fleets. However, it could also be shown that relocation strategies applied by a fleet manager or operator directly have a stronger impact than relocation constraints created through parking management strategies.

These findings show that it will be beneficial for all involved stakeholders if transport authorities take an active role in the decision on how on-demand transport services are operated in their cities. In many cases, this is not even a new role transport authorities have to take on, as current taxi services and increasingly also ride-hailing services, are also often regulated.

7.2 Limitations and Scientific Recommendations

7.2.1 Behavioural Models Including Shared Automated Vehicles

The conclusions drawn in regard to the relocation strategies of idle vehicles and parking management of shared automated vehicles are based on results obtained from agent-based simulation models. Such models allow modelling the interaction effects emerging from the interplay between the simulated agents. This interplay is defined by a set of pre-defined rules that describe the behaviour of the agents. The quality of the simulation results is thus directly linked to the accuracy of the underlying behavioural model. For the case studies simulated in this thesis, the behavioural rules are based on the concept of utility, balancing the satisfaction of performing a set of planned activities with the inconveniences of travelling. The latter consist of the related costs, the time spent on travelling and deviances in the planned activity-schedule due to delays or congestion.

Since only very few people have already experienced travelling in self-driving vehicles and nobody has used transport services operated by shared automated vehicles as sketched in this thesis, it is not yet possible to formulate a reliable behavioural model that includes SAV. For this reason, the analysis of the strategies for vehicle relocation and parking management has been confined to operational parameters while leaving out the behavioural response to the different strategies. Once, more reliable behavioural models become available, this analysis should also include the effects of vehicle relocation on the agent's choice behaviour, e.g. in regard to mode-choice.

The findings presented in the first part of this thesis add to a better understanding of the perceived preferences towards self-driving vehicles used for public transport services and car-sharing systems. However, the results for the stated preferences hold only for the particular choice situations described in the choice experiments, which do not cover all choice situations needed to describe the agent behaviour in the simulation model. Examples for choice situations not covered in the experiments are mode choices for trip purposes other than commuting, or departure-time choices. For this reason, the findings presented in the first part of this thesis are only used in a qualitative way in the simulation model of the second and third part. The findings from these studies can also not be used to predict the mode choice behaviour in the future, as they capture merely the current perceived utility of the different mode alternatives included in the experiment. Over time, with a growing degree of familiarity with the new technology and the new transport services, these perceptions are likely to change. By continuing to perform stated-preferences experiences, it will be possible to derive increasingly accurate descriptions of the perceived preferences towards vehicle automation and transport services offered by self-driving vehicles. Furthermore, by doing so we would learn more about how perceptions of new technology change over time with an increasing degree of familiarity and in the presence of possible disruptive events in the early phase of deployment, positive or negative. Monitoring the behavioural response to the introduction of self-driving vehicles will be particularly interesting once enough people have actually experienced travelling in such vehicles and with such transport services in order to compare stated and revealed preferences.

7.2.1 Modelling the Operation of Shared Automated Vehicles

The findings in this thesis are based on one possible description of how on-demand transport services operated by shared automated vehicles could look like. There are numerous operational parameters, such as the fleet size, type of vehicles, the way how vehicles are shared, the routing, dispatching or idle vehicle relocation, that determine the quality of service performance and its externalities. By performing more simulation studies for the different possible forms of transport offered by shared automated vehicles, it will be possible to detect opportunities as well as problems that generally can arise with the introduction of such services. For this, it is crucial to analyse the effects in a holistic manner that captures not just service efficiency, but also service externalities and service equity.

From the findings in this thesis, two particularly interesting questions arise for the relocation of idle vehicles in regard to operational decisions under uncertainty: how will the relocation of idle vehicles impact the performance in a setting in which (1) the fleet manager or transport operator does not have full information on the availability of free parking space at the moment of the decision to relocate a vehicle, or parking space cannot be reserved in advance, and (2) several fleets compete for passengers and parking space. Including these issues in the simulation of shared automated vehicles would not just enrich our understanding on how to best operate a fleet of such vehicles, but would also allow determining more precisely the range in which parking management can impact such transport services.

7.2.3 Modelling Car-Ownership in Times of Shared Automated Vehicles

A possible introduction of new transport services operated by shared automated vehicles would not just impact short-term decision such as mode choice or departure time choice, but could also potentially impact long-term choices such as car ownership choices. As shown in this thesis, car-sharing services or ride-hailing services, automated or not, have the potential to compete directly with the use of the private car, especially when they relieve the users of parking costs and the search for parking spots. Most of the current car ownership models make mainly use of socio-economic parameters for modelling car ownership choices. In times of car-sharing services similar to the one envisioned in this thesis, however, simple socio-economic parameters such as income and household size might not be the best predictors anymore. In order to capture the point at which a car owner considers not owning a private vehicle anymore due to his/her access to car-sharing services, the use of the private car and use of the car-sharing service could be compared. There are only few car-ownership models that include the actual use of a private car to forecast car ownership, among which the “Indirect utility car ownership and use” (De Jong, 1990; Rouwendal & Pommer, 2004) models and the “Dynamic discrete-continuous choice” models (Bhat & Sen, 2006; Cernicchiaro & de Lapparent, 2014). These joint discrete-continuous models consider car ownership and car use in integrated micro-economic frameworks, based on the idea that car ownership and car usage are strongly interrelated. For each household, a certain demand for kilometres-travelled by car is assumed, depending on the socio-economic status of the household. Additionally, an indirect-utility model describes the relationship between different car ownership states and the demand for car use. Some of these models even include fixed car cost and variable car cost into this choice set. Based on such models, the usage of car-sharing or ride-hailing services could be included in car ownership models, which would allow, in combination with models capturing the day-to-day choices like the one presented in this thesis, to model the impact of such services on long-term choices.

7.3 Outlook

Self-driving vehicles could allow operating public transport services in a more flexible manner since they could make it more affordable to operate fleets of smaller vehicles providing on-demand transport services. This has the potential to disrupt the way we perceive, use and operate public transport services and consequently presents unknown challenges to transport- and urban planners. An example of such new challenges is one of the key questions addressed in this thesis, namely if, and where, idle self-driving vehicles providing on-demand public transport services should be parked, and how much urban space should be allocated to this purpose. Given the long planning horizon common to infrastructural projects, it is now the time to start the discussion on what changes can be expected due to increasingly automated vehicles, and how these can be shaped in a beneficial way. Scientific research findings on this topic can support transport authorities and municipalities in taking an active role in transforming cities currently adapted to private cars into cities in which resources are shared more efficiently and space is used more effectively. Three research directions directly connecting to the findings in this thesis are highlighted in the following:

(1) Closing the gap between models describing short-term impacts and those describing long-term effects of the introduction of shared transport services. Without this step, it will not be possible to model the potentially far-reaching changes in travel behaviour due to such services. A brief sketch of how mode choice could be coupled to car ownership is discussed above. There are more aspects for which short-term and long-term choices affect each other, e.g. location choices and land use patterns, which need to be included as well.

(2) A second issue directly affiliated with the research presented in this thesis is the question if the technology of self-driving vehicles can be a game-changer regarding transport equity. If the introduction of self-driving vehicles should allow public transport services to become more flexible, issues of availability and accessibility of transport services can be tackled, but what will be the impact in regard to affordability and adequacy of the provided transport services? Addressing these questions, especially in regard to the role transport authorities can play in the development of such transport services, will be crucial in terms of shaping the introduction of self-driving vehicles beneficially.

(3) Finally, addressing the possible spatial impacts of self-driving vehicles on a broader scale than just parking space consumption will be important to make transport and urban planning fit for a future with self-driving vehicles. This concerns issues directly linked to the operation of SAV such as future road layouts, the installation of vehicle communication technologies or the design of transport networks integrating such transport services, but also might lead to changes in land-use, and hence urban planning in general. For example, large-scale on-demand transport services require a different infrastructure from current public transport services for picking-up and dropping-off passengers. Currently, public transport hubs often create local centres vital to the urban structure by attracting businesses and other local players of medical and social supply. With an increase in door-to-door transport services, public transport hubs could lose

their status as a natural anchor of such local centres. The changes shared automated vehicles might cause in the public transport system, therefore, open up new opportunities, as well as challenges, for urban planning.

Appendix

In chapter 5 and 6, various relocation strategies have been simulated for the "base case" of the Amsterdam MATSim Scenario, described in detail in Table 5.2. In addition to these strategies, an additional number of reactive relocation and cruising strategies was tested. An overview of all simulated strategies with a brief description is presented in Table A.1.

Table A1: Overview of the proactive and reactive relocation strategies tested for the Amsterdam case study

Proactive relocation strategies	***Demand Anticipation***	Described in chapter 5, referred to as "Base Case" in chapter 6: Vehicles move to zones with the highest demand depending on the availability of free parking space.
	Cruise	Described in chapter 6, same functionality as *Demand Anticipation*, with the difference that vehicles keep cruising in zones to which they relocate
	Supply Anticipation	Described in chapter 5: Vehicles move to zones with the lowest supply of idle vehicles depending on the availability of free parking space
	Demand-Supply Balancing	Described in chapter 5: Vehicles move to zones with the highest deficit of idle vehicles per zone to serve the future demand in zone
Reactive relocation strategies	***Remain***	Described in chapter 6: Hypothetical scenario, in which idle vehicles remain at the latest drop-off location, regardless of parking space availability
	Remain With Parking Constraints	Not presented so far: Idle vehicles drive to parking spots available within the zone of their latest drop-off location. If no parking spot is available, they move to the closest zone with available parking spots.
	Random Cruise[6]	Not presented so far: Idle vehicles cruise randomly through the network until they are assigned to a new request.

[6] The results for this relocation strategy are averaged over 8 simulation runs. Due to the volatile nature of this relocation strategy, more simulation runs are required compared to the other ones presented in this thesis (4 runs on a 99% confidence interval). For this reason, also a lower confidence interval of 90% has been selected in order to determine the necessary number of simulation runs.

An overview of the main key-performance-indicators discussed in this thesis is shown in Table A2. and graphical results for the zonal analysis are shown in Tables A3, A4 and A5. Here, this entire set of strategies is briefly compared based on the key performance indicators employed in this thesis.

Table A2: Key-performance indicators for proactive and reactive relocation strategies for idle SAV.

	Proactive relocation strategies				***Reactive relocation strategies***		
	Demand Anticipation	***Cruise***	***Supply Anticipation***	***Demand-Supply Balancing***	***Remain***	***Remain With Parking Constraints***	***Random Cruise***
Share of empty driven mileage over total driven mileage	56.1%	87.1%	57.1%	57.1%	10.2%	39.7%	78.8%
Share of driven mileage for relocation over total empty driven mileage	70.5%	95.7%	75.0%	75.2%	0%	66.7%	84.9%
Share of time driven emptily	14.0%	76.2%	14.5%	14.6%	9,7%	6.8%	26.7%
Average in-vehicle times per trip in SAV [in minutes]	18.0	18.8	18.4	18.2	15.4	15.9	48.7
Average and 95% percentile of passenger waiting time [in minutes]	4.6 ; 12.1	4.3; 9.7	3.6 ; 9.4	3.5 ; 9.1	2.2; 5.8	3.5 ; 9.9	93.2;341
Average trip time: waiting time and in-vehicle time [in minutes]	22.7	23.2	21.9	21.7	17.6	19.3	141.9
Average driving speed for SAV [in km/h]	39.2	37.6	39.2	39.1	46.4	45.4	20.1
Average driving speed of SAV with and without passengers on-board [in km/h]	38.9; 39.6	37.9; 37.6	39.3; 39.1	39.0; 39.2	46.02; 49.9	44.8; 46.5	17.4; 22.0
Total VKT of SAV [in 1000 km]	3,519	11,931	3,610	3,608	1,707	2,549	7,053
Empty VKT per SAV [in km]	158	831	165	165	14	81	445
Gini-coefficient for passenger waiting times	0.554	0.514	0.517	0.507	0.475	0.499	0.661
Gini-coefficient for average zonal passenger waiting times	0.291	0.254	0.276	0.265	0.215	0.277	0.199

Table A3: Average zonal passenger waiting times for proactive and reactive relocation strategies for idle SAV.

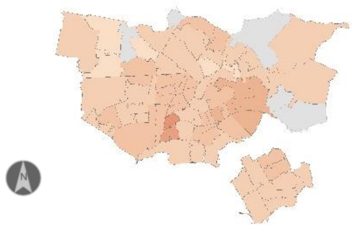
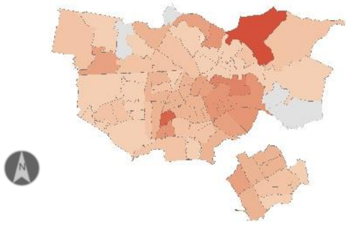
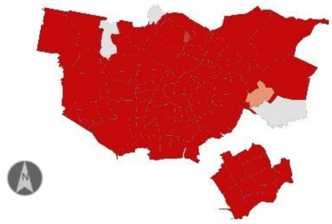
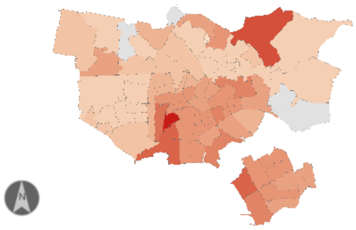
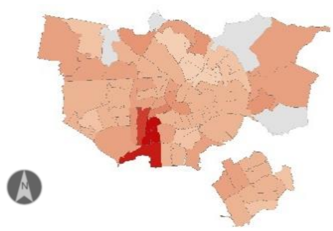
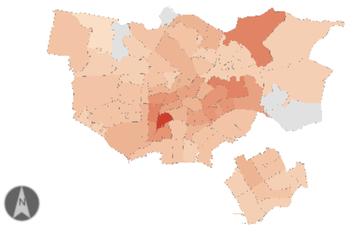
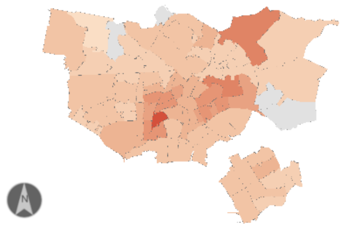
Zonal average waiting times [in minutes]	***Remain***
none 0–0.9 min 1-1.9 min 2-2.9 min 3-3.9 min 4-4.9 min 5-5.9 min 6-6.9 min 7-7.9 min 8-8.9 min 9-9.9 min 10-10.9 min 11-11.9 min 12-12.9 min ≥13 min	
Remain With Parking Constraints	***Random Cruise***
	
Demand Anticipation	***Cruise***
	
Supply Anticipation	***Demand-Supply Balancing***
	

Table A4: Average zonal parking usage for the proactive and reactive relocation strategies for idle SAV for which parking usage is applicable for the 21st hour of the simulated day.

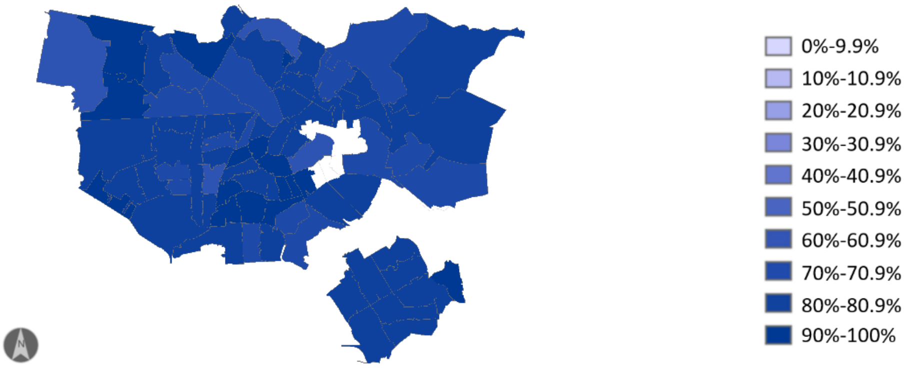
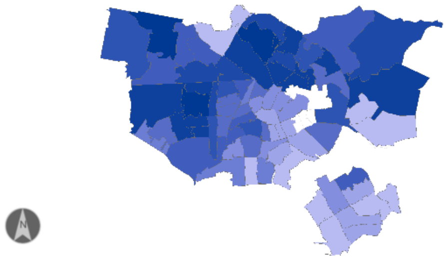
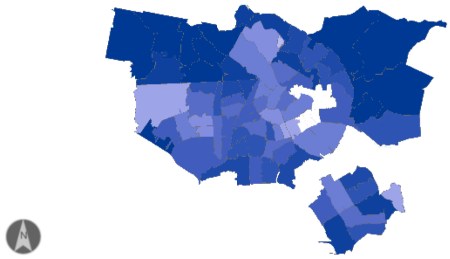
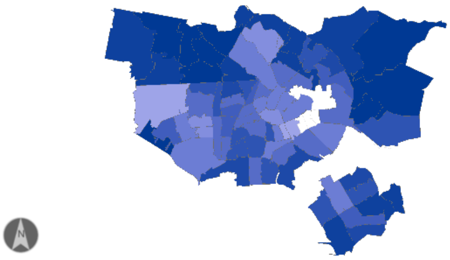
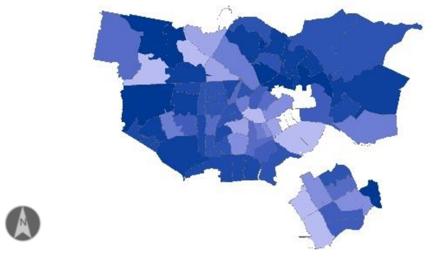
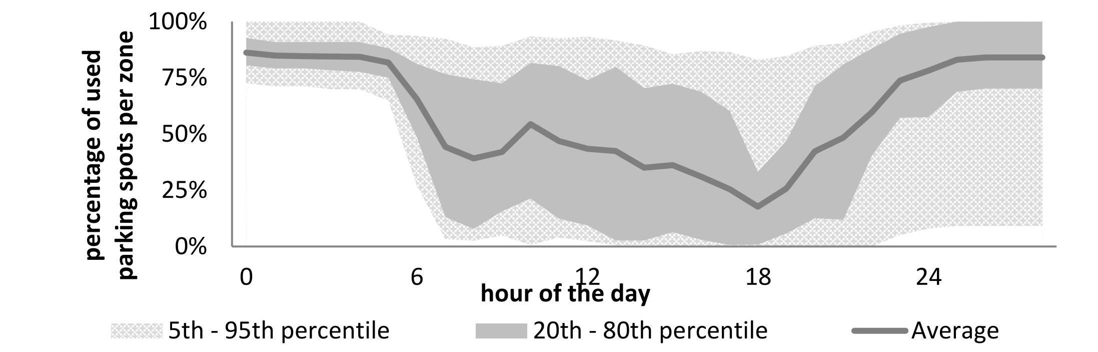
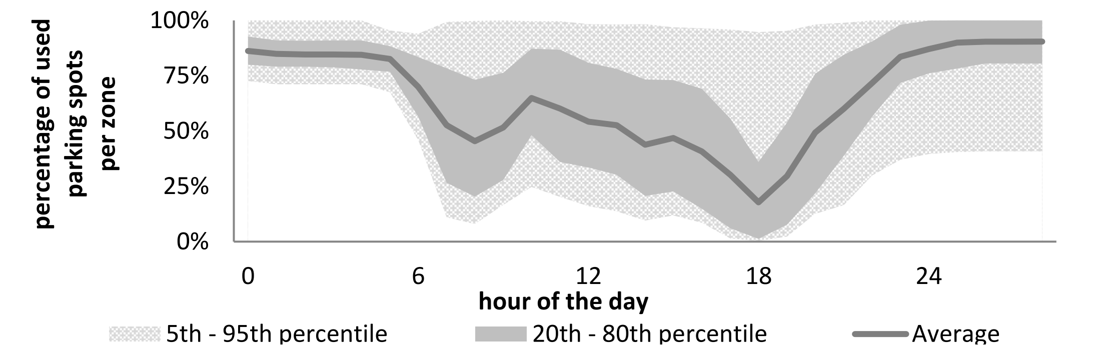
<table>
<tr><td></td><td colspan="2">Initial Parking Usage per Zone</td></tr>
<tr><td></td><td colspan="2">
</td></tr>
<tr><td rowspan="4">21h - 22h</td><td>Demand Anticipation</td><td>Supply Anticipation</td></tr>
<tr><td></td><td></td></tr>
<tr><td>Demand-Supply Balancing</td><td>Remain With Parking Constraints</td></tr>
<tr><td></td><td></td></tr>
</table>

Table A5: Average zonal parking usage (solid line) over the course of a simulated day for the proactive and reactive relocation strategies for idle SAV for which parking usage is applicable. The 5th-95th percentile and 20th-80th percentile are shown by the shaded areas.

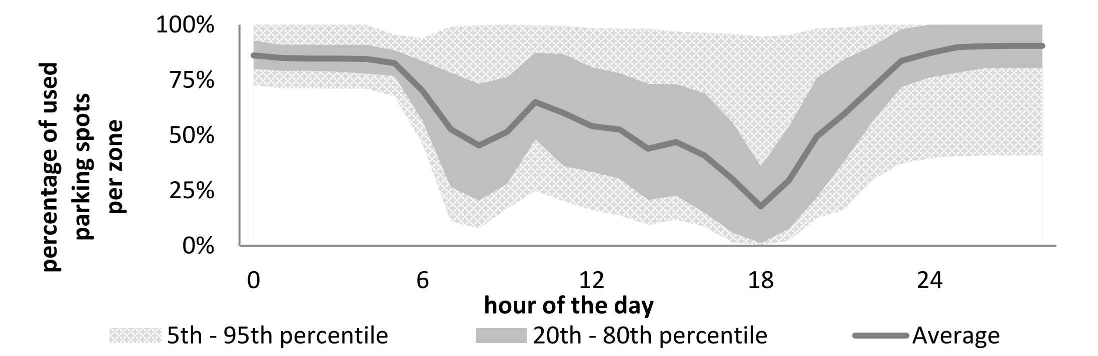
Demand Anticipation



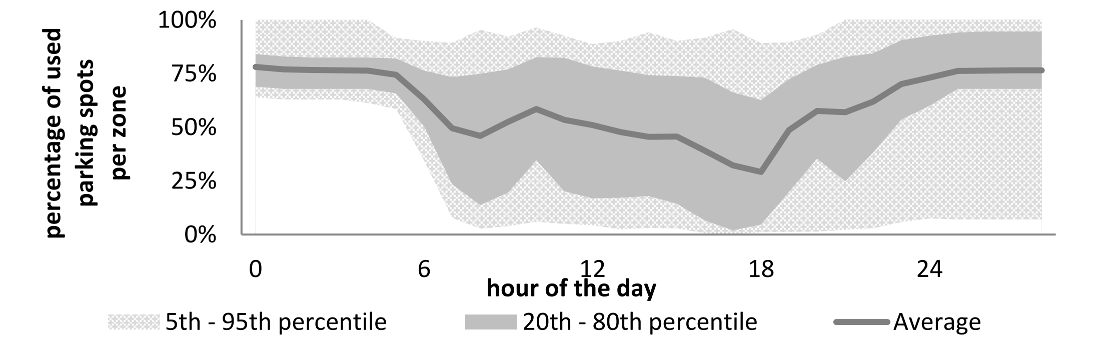
Supply Anticipation



Demand-Supply Balancing



Remain With Parking Constraints



References

Alemi, F., Circella, G., Handy, S., & Mokhtarian, P. (2018). What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California. *Travel Behaviour and Society*, *13*, 88–104. https://doi.org/10.1016/J.TBS.2018.06.002

Alessandrini, A., Delle Site, P., Stam, D., Gatta, V., Marcucci, E., & Zhang, Q. (2017). Using Repeated-Measurement Stated Preference Data to Investigate Users' Attitudes Towards Automated Buses Within Major Facilities. In J. Świątek & J. M. Tomczak (Eds.), *Advances in Systems Science* (pp. 189–199). Cham: Springer International Publishing.

Alonso-mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., & Rus, D. (2017). On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. *PNAS*, *114*(3), 462–467. https://doi.org/10.1073/pnas.1611675114/-/DCSupplemental.www.pnas.org/cgi/doi/10.1073/pnas.1611675114

Anderson, D. N. (2014). "Not just a taxi"? For-profit ridesharing, driver strategies, and VMT. *Transportation*, *41*(5), 1099–1117. https://doi.org/10.1007/s11116-014-9531-8

Anderson, J. M., Kalra, N., Stanley, K. D., Sorensen, P., Samaras, C., & Oluwatola, O. A. (2014). *Autonomous Vehicle Technology - A Guide for Policymakers*. Retrieved from https://www.rand.org/content/dam/rand/pubs/research_reports/RR400/RR443-2/RAND_RR443-2.pdf

Angelopoulos, A., Gavalas, D., Konstantopoulos, C., Kypriadis, D., & Pantziou, G. (2018). Incentivized vehicle relocation in vehicle sharing systems. *Transportation Research Part C: Emerging Technologies*, *97*, 175–193. https://doi.org/10.1016/J.TRC.2018.10.016

Arentze, T. A., & Timmermans, H. J. P. (2004). A learning-based transportation oriented simulation system. *Transportation Research Part B*, *38*(7), 613–633. https://doi.org/10.1016/j.trb.2002.10.001

Ashkrof, P., Correia, G., Cats, O., & van Arem, B. (2019). Impact of Automated Vehicles on Travel Mode Preference for Different Trip Purposes and Distances. *Transportation Research Record*, *2673*(5), 607–616. https://doi.org/10.1177/0361198119841032

Azevedo, C. L., Marczuk, K., Raveau, S., Soh, H., Adnan, M., Basak, K., … Ben-Akiva, M. (2016). Microsimulation of Demand and Supply of Autonomous Mobility On Demand. *Transportation Research Record: Journal of the Transportation Research Board*, *2564*, 21–30. https://doi.org/10.3141/2564-03

Babicheva, T., Burghout, W., Andreasson, I., & Fail, N. (2018). The matching problem of empty vehicle redistribution in autonomous taxi systems. *Procedia Computer Science*, *130*, 119–125. https://doi.org/10.1016/j.procs.2018.04.020

Bahamonde-Birke, F., & Ortuzar, J. (2015). About the Categorization of Latent Variables in Hybrid Choice Models. *Discussion Papers of DIW Berlin 1527, DIW Berlin, German Institute for Economic Research*. https://doi.org/10.2139/ssrn.2698095

Bailey, A., & Clark, T. D. (1992). Taxi Management and Route Control: A Systems Study and Simulation Experiment. In J. J. Swain, D. Goldsman, R. C. Crain, & J. R. Wilson (Eds.), *Proceedings of the 1992 Winter Simulation Conference* (pp. 1217–1223).

Balan, A., & Raina, M. (2019). Lyft follows Uber in suing NYC over cruising time caps. *Reuters*. Retrieved from https://www.reuters.com/article/us-lyft-inc-lawsuit-newyork/lyft-follows-uber-in-suing-nyc-over-cruising-time-caps-idUSKBN1WR0NG

Balmer, M., & Rieser, M. (2009). MATSim-T: Architecture and simulation times. In A. Bazzan & F. Klügl (Eds.), *Multi-Agent Systems for Traffic and Transportation Engineering* (pp. 57–78). https://doi.org/10.1140/epjb/e2008-00153-6

Bansal, P., Kockelman, K. M., & Singh, A. (2016). Assessing public opinions of and interest in new vehicle technologies: An Austin perspective. *Transportation Research Part C: Emerging Technologies*, *67*, 1–14. https://doi.org/10.1016/j.trc.2016.01.019

Barbour, N., Menon, N., Zhang, Y., & Mannering, F. (2019). Shared automated vehicles: A statistical analysis of consumer use likelihoods and concerns. *Transport Policy*, *80*, 86–93. https://doi.org/10.1016/J.TRANPOL.2019.05.013

Becker, F., & Axhausen, K. W. (2017). Literature review on surveys investigating the acceptance of autonomous vehicles. *TRB 96th Annual Meeting Compendium of Papers*, 1–12. Washington, D.C.

Becker, H., Ciari, F., & Axhausen, K. W. (2017). Comparing car-sharing schemes in Switzerland: User groups and usage patterns. *Transportation Research Part A: Policy and Practice*, *97*, 17–29. https://doi.org/10.1016/j.tra.2017.01.004

Ben-Akiva, M., McFadden, D., & Train, K. (2019). Foundations of Stated Preference Elicitation - Consumer Behavior and Choice-based Conjoint Analysis. *Foundations and Trends® in Econometrics*, *10*(1–2), 1–124. https://doi.org/http://dx.doi.org/10.1561/0800000036

Ben-Dor, G., Ben-Elia, E., & Benenson, I. (2019). Determining an Optimal Fleet Size for a Reliable Shared Automated Vehicle Ride-Sharing Service. *Procedia Computer Science*, *151*, 878–883. https://doi.org/10.1016/J.PROCS.2019.04.121

Bhat, C. R., & Sen, S. (2006). Household vehicle type holdings and usage: an application of the multiple discrete-continuous extreme value (MDCEV) model. *Transportation Research Part B: Methodological*, *40*(1), 35–53.

https://doi.org/10.1016/j.trb.2005.01.003

Bierlaire, M. (2003). BIOGEME: A free package for the estimation of discrete choice models. *Proceedings of the 3rd Swiss Transportation Research Conference, Ascona, Switzerland*.

Bierlaire, M. (2006). A theoretical analysis of the cross-nested logit model. *Annals of Operations Research, 144*(1), 287–300. https://doi.org/10.1007/s10479-006-0015-x

Bischoff, J., & Maciejewski, M. (2016). Simulation of City-wide Replacement of Private Cars with Autonomous Taxis in Berlin. *Procedia Computer Science*, *83*(Ant), 237–244. https://doi.org/10.1016/j.procs.2016.04.121

Börjesson, M., Eliasson, J., & Franklin, J. P. (2012). Valuations of travel time variability in scheduling versus mean-variance models. *Transportation Research Part B: Methodological*, *46*, 855–873. https://doi.org/10.1016/j.trb.2012.02.004

Bösch, P. M., Becker, F., Becker, H., & Axhausen, K. W. (2018). Cost-based analysis of autonomous mobility services. *Transport Policy*. https://doi.org/10.1016/j.tranpol.2017.09.005

Brown, A., & Taylor, B. D. (2018). Bridging the Gap between Mobility Haves and Have-Nots. In *Three Revolutions* (pp. 131–150). https://doi.org/10.5822/978-1-61091-906-7_6

Bundesministerium fuer Verkehr und digitale Infrastuktur. (2018). Mobilität in Deutschland. In *Mobilität in Deutschland-Ergebnisbericht*. Retrieved from http://www.mobilitaet-in-deutschland.de/pdf/MiD2017_Ergebnisbericht.pdf

Cai, H., Zhan, X., Zhu, J., Jia, X., Chiu, A. S. F., & Xu, M. (2016). Understanding taxi travel patterns. *Physica A: Statistical Mechanics and Its Applications*, *457*, 590–597. https://doi.org/10.1016/j.physa.2016.03.047

Campello-Vicente, H., Peral-Orts, R., Campillo-Davo, N., & Velasco-Sanchez, E. (2017). The effect of electric vehicles on urban noise maps. *Applied Acoustics*, *116*, 59–64. https://doi.org/10.1016/J.APACOUST.2016.09.018

Centraal Bureau voor de Statistiek (CBS). (2015). Huishoudens in bezit van auto of motor; huishoudkenmerken. Retrieved October 16, 2016, from statline.cbs.nl/StatWeb/publication/?VW=T&DM=SLNL&PA=81845NED&LA=NL

Centraal Bureau voor de Statistiek (CBS). (2016). Bevolking per maand; leeftijd, geslacht, herkomst, generatie. Retrieved June 13, 2016, from http://statline.cbs.nl/Statweb/publication/?DM=SLNL&PA=71090ned&D1=0&D2=0-1&D3=0,107,121-122&D4=0&D5=0&D6=l&HDR=T,G3,G1&STB=G2,G4,G5&VW=T

Centraal Bureau voor de Statistiek (CBS). (2018a). 4 Procent Lopend Naar Het Werk. Retrieved October 1, 2018, from https://www.cbs.nl/nl-nl/nieuws/2018/14/4-procent-lopend-naar-het-werk

Centraal Bureau voor de Statistiek (CBS). (2018b). Personenmobiliteit; aandeel van verkeersdeelnemers naar persoonskenmerken. Retrieved January 10, 2019, from https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83496NED/table?ts=1537792900954

Centraal Bureau voor de Statistiek (CBS). (2019). Personenauto's. Retrieved November 11, 2019, from CBS website: https://www.cbs.nl/nl-nl/maatschappij/verkeer-en-vervoer/transport-en-mobiliteit/infra-en-vervoermiddelen/vervoermiddelen/categorie-vervoermiddelen/personenauto-s

Cernicchiaro, G., & de Lapparent, M. (2014). A Dynamic Discrete/Continuous Choice Model for Forward-Looking Agents Owning One or More Vehicles. *Computational Economics*, *46*(1), 15–34. https://doi.org/10.1007/s10614-014-9449-4

Cetin, T., & Deakin, E. (2019). Regulation of taxis and the rise of ridesharing. *Transport Policy*, *76*, 149–158. https://doi.org/10.1016/J.TRANPOL.2017.09.002

Chen, L., Mislove, A., & Wilson, C. (2015). Peeking Beneath the Hood of Uber. *Proceedings of the 2015 Internet Measurement Conference*, 495–508. https://doi.org/10.1145/2815675.2815681

Chen, T. D., Kockelman, K. M., & Hanna, J. P. (2016). Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions. *Transportation Research Part A: Policy and Practice*, *94*, 243–254. https://doi.org/10.1016/j.tra.2016.08.020

ChoiceMetrics. (2018). *Ngene 1.2 User Manual & Reference Guide*. Australia.

Ciari, F., & Axhausen, K. W. (2012). Choosing carpooling or carsharing as a mode: Swiss stated choice experiments. *Presented at 91st Annual Meeting of the Transportation Research Board, Washington, D.C.*, 1–23.

Circella, G., & Alemi, F. (2018). Transport Policy in the Era of Ridehailing and Other Disruptive Transportation Technologies. *Advances in Transport Policy and Planning*, *1*, 119–144. https://doi.org/10.1016/BS.ATPP.2018.08.001

Conger, K. (2019). Uber's Self-Driving Cars Are Valued at $7.25 Billion by Investors. *New York Times*. Retrieved from https://www.nytimes.com/2019/04/18/technology/uber-atg-autonomous-cars-investment.html?searchResultPosition=2

Correia, G., de Looff, E., van Cranenburgh, S., Snelder, M., & van Arem, B. (2019). The impact of vehicle automation on the Value of Travel Time while performing work and leisure activities in a car: theoretical insights and results from a stated preference survey. *Transportation Research Part A*, *119*, 359–382. https://doi.org/10.1016/j.tra.2018.11.016

Cyganski, R. (2016). Automated Vehicles and Automated Driving form a Demand Modeling Perspective. In M. Maurer, J. C. Gerdes, B. Lenz, & H. Winner (Eds.), *Autonmous Driving* (pp. 233–253). https://doi.org/10.1007/978-3-662-48847-8_12

D'Acierno, L., Gallo, M., & Montella, B. (2006). Optimisation models for the urban parking pricing problem. *Transport Policy*, *13*(1), 34–48. https://doi.org/10.1016/j.tranpol.2005.08.001

Dandl, F., & Bogenberger, K. (2019). Comparing Free-Floating Carsharing Data and Simulations of Autonomous Electric Taxis in Munich. *IEEE Transactions on Intelligent Transportation Systems*, *20*(6), 2037–2047. https://doi.org/http://dx.doi.org/10.1109/TITS.2018.2857208

Dandl, F., Hyland, M., Bogenberger, K., & Mahmassani, H. S. (2019). Evaluating the impact of spatio-temporal demand forecast aggregation on the operational performance of shared autonomous mobility fleets. *Transportation*, *46*(6), 1975–1996. https://doi.org/10.1007/s11116-019-10007-9

De Jong, G. C. (1990). An indirect utility model of car ownership and private car use. *European Economic Review*, *34*(5), 971–985. https://doi.org/10.1016/0014-2921(90)90018-T

de Looff, E., Correia, G., van Cranenburgh, S., Snelder, M., & van Arem, B. (2018). Potential changes in value of travel time as a result of vehicle automation: a casestudy in the

Netherlands. *TRB 97th Annual Meeting Compendium of Papers*, *31*(15).

de Luca, S., & Di Pace, R. (2014). Modelling the Propensity in Adhering to a Carsharing System: A Behavioral Approach. *Transportation Research Procedia*, *3*, 866–875. https://doi.org/10.1016/j.trpro.2014.10.065

Dong, X., DiScenna, M., & Guerra, E. (2017). Transit user perceptions of driverless buses. *Transportation*, 35–50. https://doi.org/10.1007/s11116-017-9786-y

Dowling, R., & Kent, J. (2015). Practice and public–private partnerships in sustainable transport governance: The case of car sharing in Sydney, Australia. *Transport Policy*, *40*, 58–64. https://doi.org/10.1016/j.tranpol.2015.02.007

Drut, M. (2018). Spatial issues revisited: The role of shared transportation modes. *Transport Policy*, *66*, 85–95. https://doi.org/10.1016/j.tranpol.2018.02.003

Elliott, D., Keen, W., & Miao, L. (2019). Recent advances in connected and automated vehicles. *Journal of Traffic and Transportation Engineering (English Edition)*, *6*(2), 109–131. https://doi.org/10.1016/J.JTTE.2018.09.005

Fagnant, D. J., & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, *77*, 167–181. https://doi.org/10.1016/j.tra.2015.04.003

Fagnant, D. J., & Kockelman, K. M. (2014). The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. *Transportation Research Part C: Emerging Technologies*, *40*, 1–13. https://doi.org/10.1016/j.trc.2013.12.001

Fagnant, D. J., Kockelman, K. M., & Bansal, P. (2015). Operations of a Shared Autonomous Vehicle Fleet for the Austin, Texas market. *Transportation Research Record: Journal of the Transportation Research Board*, *4*, 98–106. https://doi.org/10.3141/2536-12

Farah, H., Erkens, S. M. J. G., Alkim, T., & van Arem, B. (2018). *Infrastructure for Automated and Connected Driving: State of the Art and Future Research Directions*. https://doi.org/10.1007/978-3-319-60934-8_16

Ferreira, M., Damas, L., Conceicao, H., Orey, P. M., Fernandes, R., & Steenkiste, P. (2014). Self-Automated Parking Lots for Autonomous Vehicles based on Vehicular Ad Hoc Networking. *2014 IEEE Intelligent Vehicles Symposium Proceedings*, (Iv), 472–479. https://doi.org/10.1109/IVS.2014.6856561

Ferrero, F., Perboli, G., Rosano, M., & Vesco, A. (2018). Car-sharing services: An annotated review. *Sustainable Cities and Society*, *37*, 501–518. https://doi.org/10.1016/J.SCS.2017.09.020

Flores, O., & Rayle, L. (2017). How cities use regulation for innovation: the case of Uber, Lyft and Sidecar in San Francisco. *Transportation Research Procedia*, *25*, 3756–3768. https://doi.org/10.1016/J.TRPRO.2017.05.232

Gemeente Amsterdam. (2016). *Amsterdamse Thermometer van de Bereikbaarheid*. Retrieved from https://www.amsterdam.nl/parkeren-verkeer/bereikbaar/thermometer/

Gemeente Amsterdam. (2018a). Increase in parking fees to improve quality of life. Retrieved April 10, 2019, from https://www.amsterdam.nl/en/news/increase-parking-fee/

Gemeente Amsterdam. (2018b). *Kerncijfers Amsterdam 2017*. Amsterdam, The Netherlands.

Gini, C. (1912). Variabilità e mutabilità, contributo allo studio delle distribuzioni e relazione statistiche. *Studi Economico-Giuridici Dell'Univ. Di Cagliari*, *3*, 1–158.

Gkartzonikas, C., & Gkritza, K. (2019). What have we learned ? A review of stated preference and choice studies on autonomous vehicles. *Transportation Research Part C*, *98*(December 2018), 323–337. https://doi.org/10.1016/j.trc.2018.12.003

Greenwald, J. M., & Kornhauser, A. (2019). It's up to us: Policies to improve climate outcomes from automated vehicles. *Energy Policy*, *127*, 445–451. https://doi.org/10.1016/J.ENPOL.2018.12.017

Guerra, E., & Morris, E. A. (2018). Cities, Automation, and the Self-parking Elephant in the Room. *Planning Theory and Practice*, *19*(2), 291–297. https://doi.org/10.1080/14649357.2017.1416776

Gurumurthy, K. M., Kockelman, K. M., & Simoni, M. D. (2019). Benefits and Costs of Ride-Sharing in Shared Automated Vehicles across Austin, Texas: Opportunities for Congestion Pricing. *Transportation Research Record*, *2673*(6), 548–556. https://doi.org/10.1177/0361198119850785

Haboucha, C. J., Ishaq, R., & Shiftan, Y. (2017). User preferences regarding autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *78*, 37–49. https://doi.org/10.1016/j.trc.2017.01.010

Hall, J. D., Palsson, C., & Price, J. (2018). Is Uber a substitute or complement for public transit? *Journal of Urban Economics*, *108*, 36–50. https://doi.org/10.1016/J.JUE.2018.09.003

Harding, S., Kandlikar, M., & Gulati, S. (2016). Taxi apps, regulation, and the market for taxi journeys. *Transportation Research Part A: Policy and Practice*, *88*(December 2014), 15–25. https://doi.org/10.1016/j.tra.2016.03.009

Harper, C. D., Hendrickson, C. T., & Samaras, C. (2018). Exploring the Economic, Environmental, and Travel Implications of Changes in Parking Choices due to Driverless Vehicles: An Agent-Based Simulation Approach. *Journal of Urban Planning and Development*, *144*(4), 04018043. https://doi.org/10.1061/(asce)up.1943-5444.0000488

Heinen, E., Maat, K., & van Wee, B. (2013). The effect of work-related factors on the bicycle commute mode choice in the Netherlands. *Transportation*, *40*(1), 23–43. https://doi.org/10.1007/s11116-012-9399-4

Hoogendoorn-Lanser, S., Schaap, N. T. W., & OldeKalter, M.-J. (2015). The Netherlands Mobility Panel: An Innovative Design Approach for Web-based Longitudinal Travel Data Collection. *Transportation Research Procedia*, *11*, 311–329. https://doi.org/10.1016/j.trpro.2015.12.027

Hörl, S., Ruch, C., Becker, F., Frazzoli, E., & Axhausen, K. W. (2019). Fleet operational policies for automated mobility: A simulation assessment for Zurich. *Transportation Research Part C: Emerging Technologies*, *102*, 20–31. https://doi.org/10.1016/J.TRC.2019.02.020

Horni, A., Nagel, K., & Axhausen, K. W. (2016). *The Multi-Agent Transport Simulation MATSim* (A. Horni, K. Nagel, & K. W. Axhausen, Eds.). https://doi.org/10.5334/baw. License: CC-BY 4.0

I-AT Interreg Automated Transport. (2019). Living Lab WEpod-crossborder. Retrieved January 10, 2019, from https://www.i-at.nl/Living-Lab-WEPOD-crossborder

International Transport Forum. (2015). *Urban Mobility System Upgrade: How shared self-*

driving cars could change city traffic. Retrieved from https://www.google.co.uk/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&cad=rja&uact=8&ved=0CCEQFjAA&url=http://www.internationaltransportforum.org/Pub/pdf/15CPB_Self-drivingcars.pdf&ei=W4ZLVcKzGIX2UsOsgYAL&usg=AFQjCNFKBn2GepTYHaVHEy_1D_8rMyJTGg&sig2=7fVZvuCP-b

Jiang, S., Chen, L., Mislove, A., & Wilson, C. (2018). On Ridesharing Competition and Accessibility : Evidence from Uber , Lyft , and Taxi. *Proceedings of the 2018 World Wide Web Conference Pages*, 863–872. https://doi.org/10.1145/3178876.3186134

Jin, S. T., Kong, H., Wu, R., & Sui, D. Z. (2018). Ridesourcing, the sharing economy, and the future of cities. *Cities*, *76*, 96–104. https://doi.org/10.1016/J.CITIES.2018.01.012

Kang, J., Hwang, K., & Park, S. (2016). Finding Factors that Influence Carsharing Usage: Case Study in Seoul. *Sustainabilty*, *8*(709), 1–12. https://doi.org/10.3390/su8080709

Kaspi, M., Raviv, T., & Tzur, M. (2014). Parking reservation policies in one-way vehicle sharing systems. *Transportation Research Part B: Methodological*, *62*, 35–50. https://doi.org/10.1016/j.trb.2014.01.006

Kent, J. L., & Dowling, R. (2016). “Over 1000 Cars and No Garage”: How Urban Planning Supports Car(Park) Sharing. *Urban Policy and Research*, *1146*(May), 1–13. https://doi.org/10.1080/08111146.2015.1077806

Kim, T. (2019). How Uber Hopes to Profit From Public Transit. *The New York Times*. Retrieved from https://www.nytimes.com/2019/05/30/opinion/uber-stock.html

Kolarova, V., Steck, F., Cyganski, R., & Trommer, S. (2018). Estimation of the value of time for autonomous driving using revealed and stated preference methods. *Transportation Research Procedia*, *31*(November), 35–46. https://doi.org/10.1016/j.trpro.2018.09.044

Kole, P. J., Löhr, A. J., Van Belleghem, F., & Ragas, A. (2017). Wear and Tear of Tyres: A Stealthy Source of Microplastics in the Environment. *International Journal of Environmental Research and Public Health*, *14*(10), 1265. https://doi.org/10.3390/ijerph14101265

Kouwenhoven, M., de Jong, G. C., Koster, P., van den Berg, V. A. C., Verhoef, E. T., Bates, J., & Warffemius, P. M. J. (2014). New values of time and reliability in passenger transport in The Netherlands. *Research in Transportation Economics*, *47*, 37–49. https://doi.org/10.1016/j.retrec.2014.09.017

KpVV CROW. (2019). Autodelen wordt steeds normaler - CROW. Retrieved November 11, 2019, from https://www.crow.nl/over-crow/nieuws/2019/september/autodelen-wordt-steeds

Krueger, R., Rashidi, T. H., & Rose, J. M. (2016a). Adoption of Shared Autonomous Vehicles-A Hybrid Choice Modeling Approach Based on a Stated-Choice Survey. *Presented at 95th Annual Meeting of the Transportation Research Board, Washington, D.C*, 20 pages.

Krueger, R., Rashidi, T. H., & Rose, J. M. (2016b). Preferences for shared autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *69*, 343–355. https://doi.org/10.1016/j.trc.2016.06.015

Kyriakidis, M., Happee, R., & de Winter, J. C. F. (2015). Public opinion on automated driving: Results of an international questionnaire among 5000 respondents.

Transportation Research Part F: Traffic Psychology and Behaviour, *32*, 127–140. Retrieved from https://www.sciencedirect.com/science/article/pii/S1369847815000777

Le Vine, S., & Polak, J. (2019). The impact of free-floating carsharing on car ownership: Early-stage findings from London. *Transport Policy*, *75*(December 2016), 119–127. https://doi.org/10.1016/j.tranpol.2017.02.004

Liljamo, T., Liimatainen, H., & Pöllänen, M. (2018). Attitudes and concerns on automated vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour*, *59*, 24–44. https://doi.org/10.1016/J.TRF.2018.08.010

Litman, T. (2014). Autonomous Vehicle Implementation Predictions: Implications for Transport Planning. *Transportation Research Board Annual Meeting*, *42*(2014), 36–42. https://doi.org/10.1613/jair.301

Maciejewski, M. (2016). Dynamic Transport Services. In A. Horni, K. Nagel, & K. W. Axhausen (Eds.), *The Multi-Agent Transport Simulation MATSim* (pp. 145–152). https://doi.org/10.5334/baw.23. License: CC-BY 4.0

Maciejewski, M., & Bischoff, J. (2015). Large-scale Microscopic Simulation of Taxi Services. *Procedia Computer Science*, *52*(Ant), 358–364. https://doi.org/10.1016/j.procs.2015.05.107

Maciejewski, M., & Bischoff, J. (2018). Congestion effects of autonomous taxi fleets. *Transport*, *33*(4), 971–980. https://doi.org/https://doi.org/10.3846/16484142.2017.1347827

Maciejewski, M., Bischoff, J., & Nagel, K. (2016). An Assignment-Based Approach to Efficient Real-Time City-Scale Taxi Dispatching. *Intelligent Systems IEEE*, *31*(1), 68–77. https://doi.org/10.1109/MIS.2016.2

Madigan, R., Louw, T., Dziennus, M., Graindorge, T., Ortega, E., Graindorge, M., & Merat, N. (2016). Acceptance of Automated Road Transport Systems (ARTS): An Adaptation of the UTAUT Model. *Transportation Research Procedia*, *14*, 2217–2226. https://doi.org/10.1016/j.trpro.2016.05.237

Migliore, M., Burgio, A. Lo, & Di Giovanna, M. (2014). Parking Pricing for a Sustainable Transport System. *Transportation Research Procedia*, *3*(July), 403–412. https://doi.org/10.1016/j.trpro.2014.10.021

Millard-Ball, A. (2019). The autonomous vehicle parking problem. *Transport Policy*, *75*, 99–108. https://doi.org/10.1016/J.TRANPOL.2019.01.003

Millard-Ball, A., Murray, G., Ter Schure, J., Fox, C., & Burkhardt, J. (2005). *Car-Sharing: Where and How it Succeeds*. Retrieved from Transportation Research Board website: http://onlinepubs.trb.org/onlinepubs/tcrp/tcrp_rpt_108.pdf

Mingardo, G., van Wee, B., & Rye, T. (2015). Urban parking policy in Europe: A conceptualization of past and possible future trends. *Transportation Research Part A: Policy and Practice*, *74*, 268–281. https://doi.org/10.1016/j.tra.2015.02.005

Ministry of Transport Public Works and Water Management. (2009). *Cycling in the Netherlands*. Retrieved from http://www.fietsberaad.nl/library/repository/bestanden/CyclingintheNetherlands2009.pdf

Molenda, I., & Sieg, G. (2013). Residential parking in vibrant city districts. *Economics of Transportation*, *2*(4), 131–139. https://doi.org/10.1016/j.ecotra.2014.02.002

Mounce, R., & Nelson, J. D. (2019). On the potential for one-way electric vehicle car-sharing in future mobility systems. *Transportation Research Part A: Policy and Practice*, *120*, 17–30. https://doi.org/10.1016/J.TRA.2018.12.003

Nagel, K., Kickhoefer, B., Horni, A., & Charypar, D. (2016). A Closer Look at Scoring. In A. Horni, K. Nagel, & K. W. Axhausen (Eds.), *The Multi-Agent Transport Simulation MATSim* (pp. 23–34). https://doi.org/dx.doi.org/10.5334/baw.3. License: CC-BY 4.0

Nazari, F., Noruzoliaee, M., & Mohammadian, A. (2018). Shared versus private mobility: Modeling public interest in autonomous vehicles accounting for latent attitudes. *Transportation Research Part C: Emerging Technologies*, *97*, 456–477. https://doi.org/10.1016/J.TRC.2018.11.005

Nijland, H., & van Meerkerk, J. (2017). Mobility and environmental impacts of car sharing in the Netherlands. *Environmental Innovation and Societal Transitions*, *23*, 84–91. https://doi.org/10.1016/j.eist.2017.02.001

Nordhoff, S., de Winter, J., Kyriakidis, M., Van Arem, B., & Happee, R. (2018). Acceptance of Driverless Vehicles: Results from a Large Cross-National Questionnaire Study. *Journal of Advanced Transportation*, 1–22. https://doi.org/10.1155/2018/5382192

Nordhoff, S., van Arem, B., & Happee, R. (2016). Conceptual Model to Explain, Predict, and Improve User Acceptance of Driverless Podlike Vehicles. *Transportation Research Record: Journal of the Transportation Research Board*, *2602*, 60–67. Retrieved from http://docs.trb.org/prp/16-5526.pdf

Nourinejad, M., Bahrami, S., & Roorda, M. J. (2018). Designing parking facilities for autonomous vehicles. *Transportation Research Part B: Methodological*, *109*, 110–127. https://doi.org/10.1016/J.TRB.2017.12.017

Nunes, A., & Hernandes, K. D. (2019). Autonomous Vehicles and Public Health: High Cost or High Opportunity Cost? *Pre-Print*.

OpenStreetMap Contributors. (2018). OpenStreetMap. Planet dump retrieved from https://planet.osm.org. In *Planet dump retrieved from https://planet.osm.org*. Retrieved from https://planet.openstreetmap.org/

Paundra, J., Rook, L., van Dalen, J., & Ketter, W. (2017). Preferences for car sharing services: Effects of instrumental attributes and psychological ownership. *Journal of Environmental Psychology*, *53*, 121–130. https://doi.org/10.1016/j.jenvp.2017.07.003

Payre, W., Cestac, J., & Delhomme, P. (2014). Intention to use a fully automated car: Attitudes and a priori acceptability. *Transportation Research Part F: Traffic Psychology and Behaviour*, *27*, 252–263. https://doi.org/10.1016/J.TRF.2014.04.009

Piao, J., McDonald, M., Hounsell, N., Graindorge, M., Graindorge, T., & Malhene, N. (2016). Public Views towards Implementation of Automated Vehicles in Urban Areas. *Transportation Research Procedia*, *14*, 2168–2177. https://doi.org/10.1016/J.TRPRO.2016.05.232

Pierce, G., & Shoup, D. (2013). Getting the Prices Right. *Journal of the American Planning Association*, *79*(1), 67–81. https://doi.org/10.1080/01944363.2013.787307

Regional Plan Association (RPA). (2017). *New Mobility: Autonomous Vehicles and the Regio*. Retrieved from http://library.rpa.org/pdf/RPA-New-Mobility-Autonomous-Vehicles-and-the-Region.pdf

Rouwendal, J., & Pommer, J. (2004). An indirect utility model of multiple Car Ownership and Use. In *Tinbergen Institue Discussion Paper* (Vol. 85). https://doi.org/10.1016/0014-

2921(90)90018-T

Ruehl, M. (2019). China’s Didi Chuxing spins out self-driving car unit | Financial Times. Retrieved August 22, 2019, from Financial Times website: https://www.ft.com/content/3beda7a8-b752-11e9-96bd-8e884d3ea203

SAE International. (2018). *Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles*. Retrieved from https://saemobilus.sae.org/content/j3016_201806

Sayarshad, H. R., & Chow, J. Y. J. (2017). Non-myopic relocation of idle mobility-on-demand vehicles as a dynamic location-allocation-queueing problem. *Transportation Research Part E: Logistics and Transportation Review*, *106*, 60–77. https://doi.org/10.1016/j.tre.2017.08.003

Schmöller, S., Weikl, S., Müller, J., & Bogenberger, K. (2015). Empirical analysis of free-floating carsharing usage: The Munich and Berlin case. *Transportation Research Part C: Emerging Technologies*, *56*, 34–51. https://doi.org/10.1016/j.trc.2015.03.008

Schoettle, B., & Sivak, M. (2014). *A Survey of Public Opinion About Autonomous and Self-Driving Vehicles in the U.S., the U.K., and Australia (Report No. UMTRI-2014-21).*

Shaheen, S. (2018). Shared Mobility: The Potential of Ridehailing and Pooling. In *Three Revolutions* (pp. 55–76). https://doi.org/10.5822/978-1-61091-906-7_3

Shaheen, S. A., Cohen, A. P., & Martin, E. (2010). Carsharing Parking Policy - Review of North American Practices and San Francisco, California, Bay Area Case Study. In *Transportation Research Record* (Vol. 2187). https://doi.org/10.3141/2187-19

Shaheen, S., Bansal, A., Chan, N., & Cohen, A. (2017). Mobility and the Sharing Economy: Industry Developments and Early Understanding of Impacts. *UC Berkeley: Transportation Sustainability Research Center*. https://doi.org/10.7922/G24F1NXC

Shoup, D. (2018). *Parking and the City* (D. Shoup, Ed.). https://doi.org/10.4324/9781351019668

Simićević, J., Vukanović, S., & Milosavljević, N. (2013). The effect of parking charges and time limit to car usage and parking behaviour. *Transport Policy*, *30*, 125–131. https://doi.org/10.1016/j.tranpol.2013.09.007

Simoni, M. D., Kockelman, K. M., Gurumurthy, K. M., & Bischoff, J. (2019). Congestion pricing in a world of self-driving vehicles: An analysis of different strategies in alternative future scenarios. *Transportation Research Part C: Emerging Technologies*, *98*, 167–185. https://doi.org/10.1016/J.TRC.2018.11.002

Somerville, H. (2018). Lyft surpasses 5,000 self-driving rides with Aptiv fleet - Reuters. Retrieved August 22, 2019, from Reuters website: https://www.reuters.com/article/us-lyft-selfdriving/lyft-surpasses-5000-self-driving-rides-with-aptiv-fleet-idUSKCN1L61AX

Span, P. (2019). Older People Need Rides. Why Aren’t They Using Uber and Lyft? - The New York Times. Retrieved August 22, 2019, from The New York Times website: https://www.nytimes.com/2019/08/16/health/uber-lyft-elderly.html

Sperling, D., van der Meer, E., & Pike, S. (2018). Vehicle Automation: Our Best Shot at a Transportation Do-Over? In *Three Revolutions* (pp. 77–108). https://doi.org/10.5822/978-1-61091-906-7_4

Spurling, N. (2020). Parking futures: The relationship between parking space, everyday life and travel demand in the UK. *Land Use Policy*, *91*. https://doi.org/10.1016/j.landusepol.2019.02.031

Spurlock, C. A., Sears, J., Wong-Parodi, G., Walker, V., Jin, L., Taylor, M., … Todd, A. (2019). Describing the users: Understanding adoption of and interest in shared, electrified, and automated transportation in the San Francisco Bay Area. *Transportation Research Part D: Transport and Environment*, *71*, 283–301. https://doi.org/10.1016/J.TRD.2019.01.014

statista. (2019). Number of registered car sharing users in Germany from 2008 to 2019. Retrieved November 11, 2019, from https://www.statista.com/statistics/415635/car-sharing-registered-users-gemany/

Stocker, A., & Shaheen, S. (2017). *Shared Automated Vehicles: Review of Business Models*. Paris, France.

Vahidi, A., & Sciarretta, A. (2018). Energy saving potentials of connected and automated vehicles. *Transportation Research Part C: Emerging Technologies*, *95*, 822–843. https://doi.org/10.1016/J.TRC.2018.09.001

van Engelen, M., Cats, O., Post, H., & Aardal, K. (2018). Enhancing flexible transport services with demand-anticipatory insertion heuristics. *Transportation Research Part E: Logistics and Transportation Review*, *110*(December 2017), 110–121. https://doi.org/10.1016/j.tre.2017.12.015

van Ommeren, J., & Russo, G. (2014). Time-varying parking prices. *Economics of Transportation*, *3*(2), 166–174. https://doi.org/10.1016/j.ecotra.2014.05.001

van Ommeren, K., Lelieveld, M., de Pater, M., & Goedhart, W. (2012). *Maatschappelijke kosten en baten van de fiets*. Amsterdam and The Hague, the Netherlands.

Walker, J. L., Wang, Y., Thorhauge, M., & Ben-Akiva, M. (2015). *D-Efficient OR Deficient? A Robustness Analysis of SP Experimental Designs in a VOT Estimation Context*. 18 pages. Presented at the 94th Annual Meeting of the Transportation Research Board, Washington, DC.

Weikl, S., & Bogenberger, K. (2013). Relocation strategies and algorithms for free-floating car sharing systems. *IEEE Intelligent Transportation Systems Magazine*, *5*(4), 100–111. https://doi.org/10.1109/MITS.2013.2267810

Wen, C.-H., Wang, W.-C., & Fu, C. (2012). Latent class nested logit model for analyzing high-speed rail access mode choice. *Transportation Research Part E: Logistics and Transportation Review*, *48*(2), 545–554. https://doi.org/10.1016/J.TRE.2011.09.002

Winter, K., Cats, O., Correia, G., & van Arem, B. (2018). Performance analysis and fleet requirements of automated demand-responsive transport systems as an urban public transport service. *International Journal of Transportation Science and Technology*, *7*(2), 151–167. https://doi.org/10.1016/j.ijtst.2018.04.004

Winter, K., Cats, O., Marten, K., & van Arem, B. (2019). Relocating Shared Automated Vehicles Under Parking Constraints: Effects on Service Efficiency, Externalities and Equity. *Under Review*.

Winter, K., Cats, O., Martens, K., & van Arem, B. (2017). A Stated Choice Experiment on Mode Choice in an Era of Free-Floating Carsharing and Shared Autonomous Vehicles. *Transportation Research Board, 96th Annual Meeting*, (1), 1–17. https://doi.org/10.4121/uuid:4ac4d7b7-c8b0-42ec-a096-55a4f1837585

Winter, K., Cats, O., van Arem, B., & Martens, K. (2017). Impact of relocation strategies for a fleet of shared automated vehicles on service efficiency, effectiveness and externalities. *5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems, MT-ITS 2017 - Proceedings*, 844–849. https://doi.org/10.1109/MTITS.2017.8005630

Winter, K., & Narayan, J. (2019). *Amsterdam Scenario MATSim*. https://doi.org/10.4121/uuid:6108ed85-7b24-455e-bd95-89d84e6306fa

Wong, R. C. P., Szeto, W. Y., & Wong, S. C. (2014). Bi-level decisions of vacant taxi drivers traveling towards taxi stands in customer-search: Modeling methodology and policy implications. *Transport Policy*, *33*, 73–81. https://doi.org/10.1016/j.tranpol.2014.02.011

Wright, S., Emele, C. D., Fukumoto, M., Velaga, N. R., & Nelson, J. D. (2014). The design, management and operation of flexible transport systems: Comparison of experience between UK, Japan and India. *Research in Transportation Economics*, *48*, 330–338. https://doi.org/10.1016/j.retrec.2014.09.060

Yap, M. D., Correia, G., & van Arem, B. (2016). Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. *Transportation Research Part A: Policy and Practice*, *94*, 1–16. https://doi.org/10.1016/j.tra.2016.09.003

Ye, L., & Yamamoto, T. (2019). Evaluating the impact of connected and autonomous vehicles on traffic safety. *Physica A: Statistical Mechanics and Its Applications*, *526*, 121009. https://doi.org/10.1016/J.PHYSA.2019.04.245

Yoon, T., Cherry, C. R., & Jones, L. R. (2017). One-way and round-trip carsharing: A stated preference experiment in Beijing. *Transportation Research Part D: Transport and Environment*, *53*, 102–114. https://doi.org/10.1016/J.TRD.2017.04.009

Young, M., & Farber, S. (2019). The who, why, and when of Uber and other ride-hailing trips: An examination of a large sample household travel survey. *Transportation Research Part A: Policy and Practice*, *119*, 383–392. https://doi.org/10.1016/J.TRA.2018.11.018

Zakharenko, R. (2016). Self-driving cars will change cities. *Regional Science and Urban Economics*, *61*(October 2015), 26–37. https://doi.org/10.1016/j.regsciurbeco.2016.09.003

Zhang, R., & Pavone, M. (2016). Control of robotic mobility-on-demand systems: A queueing-theoretical perspective. *The International Journal of Robotics Research*, *35*(1–3), 186–203. https://doi.org/10.1177/0278364915581863

Zhang, R., Rossi, F., & Pavone, M. (2016). Model Predictive Control of Autonomous Mobility-on-Demand Systems. *International Conference on Robotics and Automation*, 1382–1389. https://doi.org/10.1109/ICRA.2016.7487272

Zhang, W., Guhathakurta, S., Fang, J., & Zhang, G. (2015). Exploring the impact of shared autonomous vehicles on urban parking demand: An agent-based simulation approach. *Sustainable Cities and Society*, *19*, 34–45. https://doi.org/10.1016/j.scs.2015.07.006

Zheng, Z., Rasouli, S., & Timmermans, H. (2018). Modeling taxi driver anticipatory behavior. *Computers, Environment and Urban Systems*, *69*, 133–141. https://doi.org/10.1016/j.compenvurbsys.2018.01.008

Zvolska, L., Lehner, M., Voytenko Palgan, Y., Mont, O., & Plepys, A. (2018). Urban sharing in smart cities: the cases of Berlin and London. *Local Environment - The International*

Journal of Justice and Sustainability, *24*(7), 628–645. https://doi.org/10.1080/13549839.2018.1463978

Summary

Synergies between Vehicle Automation and Vehicle Sharing

Self-driving vehicles (levels 4 and 5 in the SAE classification) are predicted to possess distinctive characteristics that could change the way we use road infrastructure and the way we travel. With the introduction of such vehicles, especially the concept of sharing vehicles could become easier and more economical. Car-sharing is often discussed as a solution to the problem of private vehicles aggravating the competition for urban space, as such cars are used more efficiently and thus require less space for parking when idle. However, introducing highly automated, and hence also highly connected vehicles, is costly, as this requires infrastructural changes as well as substantial investments in the on-going development of the technology required for automating vehicles. By establishing such vehicles as a large, centralized fleet, which is used in a shared manner, investment costs could drop, and the difficult phase of mixed-traffic consisting of vehicles with different degrees automatic could be cut short. Further synergies between sharing vehicles and automating vehicles are, that self-driving vehicles could solve issues currently linked to ride-hailing services, such as driver non-compliance, and car sharing systems, such as the relocation of idle vehicles or the exclusion of user-groups based on the prerequisite of a driving licence.

The main objective of this dissertation is to understand better what it means to deploy shared automated vehicles (SAV) for on-demand public transport services. This is analysed from the perspective of three main stakeholders (see Figure I.A): (1) the preferences of potential users, (2) the fleet operation supervised by the fleet manager (3) and potential parking management strategies issued by a transport authority concerned with the introduction of SAV. In particular, the following overarching research questions are addressed:

(1) Who might use self-driving vehicles deployed in road-bound public transport services (automated buses or SAV) and what influences the choices for or against such services?
(2) What role can the relocation of idle vehicles play in the operation of SAV?
(3) How can parking management effectively shape the way SAV perform in our cities?

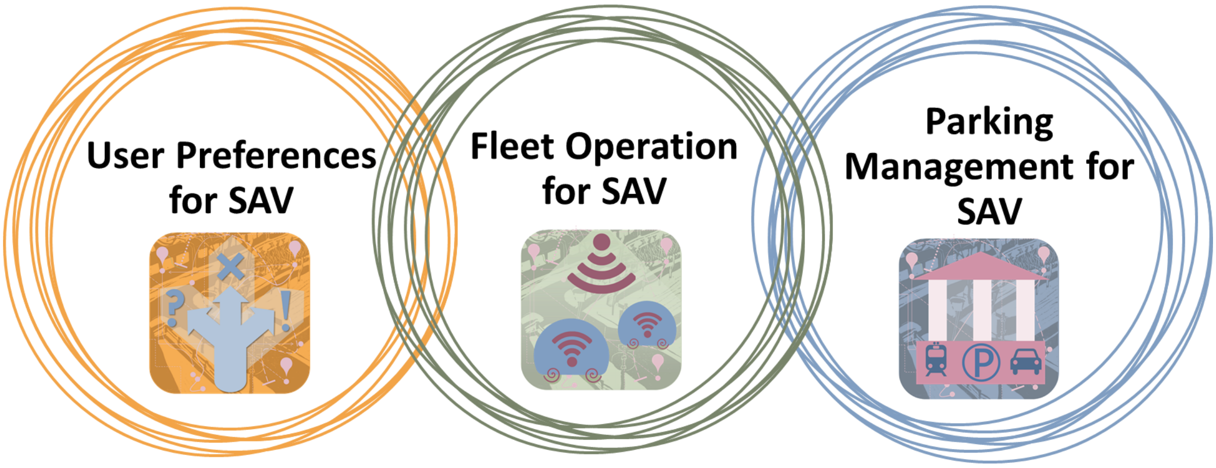


Figure I.A: Core topics addressed in this thesis: user preferences, fleet operation and parking management for SAV

User Preference: Perception of SAV and Automated Buses

Self-driving vehicles are not yet available for the kind of on-demand transport services sketched in this thesis. For this reason, we rely on stated-preference studies to better understand how potential users perceive such transportation services. This thesis features two discrete choice models capturing the relative preferences towards automated vehicles used for public transport services, one focusing on self-driving buses, the other on shared automated vehicles and free-floating car-sharing services. In the first model, a Mixed Logit model including attitudes towards self-driving buses has been estimated, in which different operational attributes in regard to the flexibility of the service (schedule based or on-demand service) or the safety standards (presence of a steward, on-board surveillance system) are introduced. The second model is estimated as a Nested Logit model with latent classes. The findings from these two stated-preference experiments suggest that currently there is a divide between those generally characterized as “early-adopters” of technology and those more hesitant towards such changes. Younger people, men, people with higher education, people preferring travel-time reduction over travel-cost reduction, people having a higher level of trust in vehicle automation or showing a generally increased interest in technology and multi-modal commuters have been found to have the highest preference for vehicle automation for public transport vehicles. Vehicle sharing in form of (non-automated) free-floating car-sharing, has been found to appeal to commuters currently commuting solely by car, in particular if they have to pay parking fees or if finding a parking spot is more difficult for private cars than for shared cars.

Fleet Operation: Relocation of Idle SAV

The operation of on-demand transport services such as the one operated by SAV envisioned here can be broken down into smaller operational problems. In this thesis, the focus is put on the operational step of idle vehicle relocation . By means of an agent-based simulation model (MATSim), different relocation rationales such as demand-anticipatory strategies and supply-anticipatory strategies are tested. The first leads to vehicle bunching around demand-hotspots, the latter leads to a more even distribution of idle vehicles in the network. The relocation strategies are analysed in a holistic manner, taking into account the service efficiency, the service provision equity and the service externalities. None of the tested relocation strategies is superior across the board. From an operational perspective, the efficiency of the service is the prime performance measure. The most advantageous strategy in this regard has been shown to be the strategy of spreading out idle vehicles throughout the network: doing so causes less congestion around demand-hotspots, which reduces passenger waiting and thus the quality of the service. However, this comes at the cost of higher total vehicle-kilometres-travelled, reducing the efficiency of the service to some degree.

Parking Management: Strategies for SAV

This thesis contributes to the exploration of potential opportunities and threats stemming from the introduction of self-driving vehicles to our cities, and what actions planning authorities could take accordingly. In particular, the impact of parking management on the service efficiency, the service externalities and the service provision equity is quantified for a set of scenarios, which are again tested by means of an agent-based simulation model. The findings suggest that, overall, it is also beneficial for transport authorities to ensure that idle vehicles are spread out as evenly as possible in the network. This can reduce the average passenger waiting times, but also increase the service provision equity, induce less congestion and lead to a more even usage of the dedicated parking facilities. However, the additional vehicle-kilometres-travelled caused by this relocation strategy contribute to more undesired service externalities. One way of spreading vehicles out more equally across the city by parking management is to reduce the ratio of parking spots per vehicle. The results of the simulation studies show that reducing the number of dedicated parking spots can improve the quality of the service even more than increasing the fleet size.

Conclusion

Self-driving vehicles could make the operation of public transport services in a more flexible manner more affordable. Introducing shared automated vehicles would allow operating a fleet of smaller vehicles providing on-demand transport services. This could potentially impact the way we use and operate public transport services, which could eventually trigger changes in car ownership or land use. Such changes can pose a unique opportunity for transport authorities and municipalities to re-organize transport supply and networks, as well as urban space, if they take an active role in guiding the way self-driving vehicles are introduced. In this thesis, it is shown that parking can be an important parameter in this process: parking fees and parking search time are shown to influence mode preferences, idle vehicle relocation is shown to impact service efficiency, service externalities and service provision equity, and parking management is shown to be an effective way for transport authorities to regulate the self-driving vehicles.

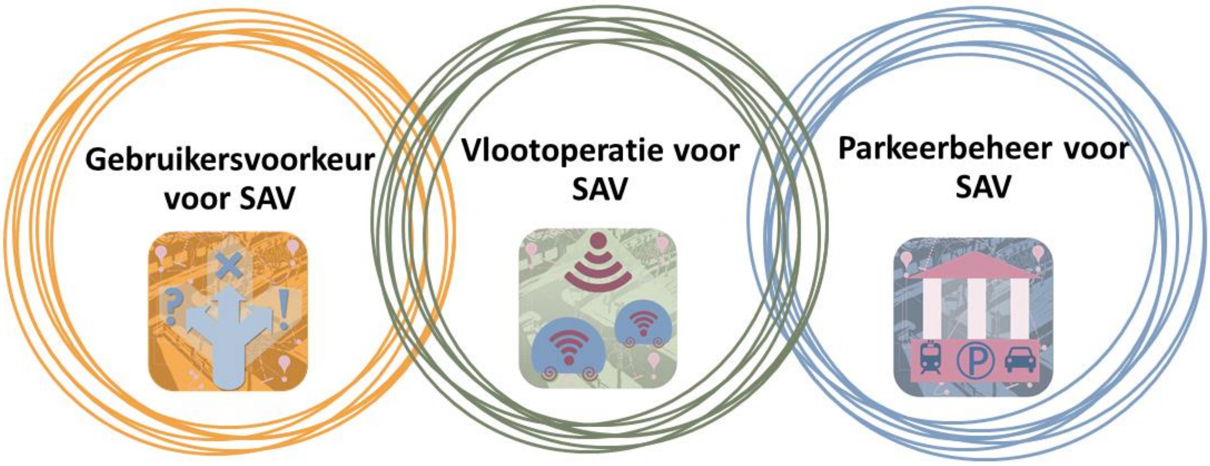
Samenvatting

Synergieën tussen voertuigautomatisering en voertuigdeling

Van zelfrijdende voertuigen (niveaus 4 en 5 in de SAE-classificatie) wordt voorspeld dat ze specifieke kenmerken bezitten, die de manier waarop we weginfrastructuur gebruiken en onze manier van reizen kunnen veranderen. Met de introductie van dergelijke voertuigen kan met name het concept van het delen van voertuigen eenvoudiger en goedkoper worden. Autodelen wordt vaak gezien als een oplossing voor het probleem van particuliere voertuigen die de druk op de stedelijke ruimte verhogen, omdat gedeelde auto's efficiënter worden gebruikt en dus minder ruimte nodig hebben om te parkeren wanneer ze niet worden gebruikt. Het introduceren van sterk geautomatiseerde, en dus ook sterk verbonden voertuigen, is echter duur, omdat dit infrastructurele veranderingen vereist, evenals substantiële investeringen in de voortdurende ontwikkeling van de technologie die nodig is voor het automatiseren van voertuigen. Door voertuigen te introduceren als een grote, gecentraliseerde vloot, die op een gedeelde manier wordt gebruikt, kunnen de investeringskosten dalen en kan de moeilijke fase van gemengd verkeer, bestaande uit voertuigen met verschillende graden van autonomie, worden ingekort. Verdere synergieën tussen het delen van voertuigen en het automatiseren van voertuigen zijn dat zelfrijdende voertuigen zowel problemen kunnen oplossen die momenteel verbonden zijn met ride-hailing-services, zoals het overtredend gedrag van bestuurders, als met deelautosystemen, zoals de verplaatsing van stilstaande voertuigen of de uitsluiting van groepen van gebruikers op basis van het bezit van een rijbewijs.

Het hoofddoel van dit proefschrift is om beter te begrijpen wat het betekent om gedeelde geautomatiseerde voertuigen (SAV) in te zetten voor on-demand openbaar vervoersdiensten. Dit wordt geanalyseerd vanuit het perspectief van drie belangrijke belanghebbenden (zie figuur IIA): (1) de gebruikersvoorkeuren van potentiële gebruikers, (2) de operatie onder toezicht van de vlootbeheerder (3) en mogelijke parkeerbeheerstrategieën uitgegeven door een transportautoriteit die betrokken is bij de introductie van SAV. In het bijzonder worden de volgende overkoepelende onderzoeksvragen behandeld:

(1) Wie is de mogelijke gebruiker van zelfrijdende voertuigen, die worden ingezet bij weggebonden openbaarvervoerdiensten (geautomatiseerde bussen of SAV), en wat beïnvloedt de keuzes voor of tegen dergelijke diensten?
(2) Welke rol kan de verplaatsing of herverdeling van stilstaande voertuigen spelen bij de operatie van SAV?
(3) Hoe kan parkeerbeheer de prestatie van SAV in onze steden effectief beïnvloeden?



Figuur II.A: Hoofdonderwerp in deze proefschrift: gebruikersvoorkeur, vlootoperatie en parkeerbeheer voor SAV.

Gebruikersvoorkeur: perceptie van SAV en geautomatiseerde bussen

Zelfrijdende voertuigen zijn nog niet beschikbaar voor het soort on-demand transportdiensten dat in dit proefschrift wordt geschetst. Om deze reden vertrouwen we op studies met vaste voorkeuren om beter te begrijpen hoe potentiële gebruikers dergelijke transportdiensten ervaren. Dit proefschrift bevat twee discrete keuzemodellen (discrete choice models) die de relatieve voorkeuren voor geautomatiseerde voertuigen weergeven, die gebruikt worden voor openbaarvervoersdiensten, waarvan één gericht is op zelfrijdende bussen en de andere op gedeelde geautomatiseerde voertuigen en free-floating autodeelservices. In het eerste model, een Mixed Logit-model waarin houdingen ten opzichte van zelfrijdende bussen zijn geschat, zijn verschillende operationele kenmerken met betrekking tot de flexibiliteit van de service (met dienstregeling of on-demand service) of de veiligheidsnormen (aanwezigheid van een steward, bewakingssysteem aan boord) ingevoerd. Het tweede model is geschat als een nested Logit-model met latent classes. De uitslag van deze twee stated-preference experimenten suggereren dat er momenteel een kloof bestaat tussen degenen die doorgaans worden gekenmerkt als "early-adopters" van technologie en degenen die aarzelen ten aanzien van dergelijke veranderingen. Jongere mensen, mannen, mensen met een hogere opleiding, mensen die een reductie in reistijd voorkeur geven boven reiskostenreductie, mensen die meer vertrouwen hebben in voertuigautomatisering of een algemeen verhoogde interesse tonen in technologie en multimodale pendelaars blijken de hoogste voorkeur te hebben voor geautomatiseerd openbaar vervoer. Het delen van voertuigen in de vorm van (niet-geautomatiseerd) free-floating autodelen blijkt aantrekkelijk te zijn voor forensen die momenteel alleen met de auto pendelen, met name als ze parkeergelden moeten betalen of als het vinden van een parkeerplaats moeilijker is voor privé auto's dan voor deelauto's.

Vlootoperatie: verplaatsing of herverdeling van niet gebruikte SAV

De operatie van on-demand vervoersdiensten, zoals die hier omschreven voor SAV, kan worden onderverdeeld in kleinere operationele problemen. In dit proefschrift wordt de nadruk gelegd op de operationele stap van de verplaatsing of herverdeling van inactieve voertuigen. Door middel van een agent-based simulatiemodel (MATSim), worden verschillende herverdelingsprincipes zoals vraag-anticiperende strategieën en aanbod-anticiperende strategieën getest. De eerste leidt tot voertuigbundeling rond vraag-hotspots, de laatste leidt tot een meer gelijkmatige verdeling van inactieve voertuigen in het netwerk. De verplaatsingsstrategieën worden op een holistische manier geanalyseerd door rekening te houden met de service-efficiëntie, de rechtvaardigheid van de dienstverlening en de externaliteiten van de dienstverlening. Geen van de geteste verplaatsingsstrategieën is algemeen superieur. Vanuit operationeel perspectief is de efficiëntie van de service de belangrijkste prestatiemaatstaf. De meest voordelige strategie in dit opzicht is de strategie om stationaire voertuigen over het netwerk te verspreiden: dit veroorzaakt minder file rond vraag-hotspots, wat de wachttijden van passagiers verhoogt en dus de kwaliteit van de service vermindert. Dit gaat echter ten koste van een hoger aantal totaal afgelegde voertuigkilometers, waardoor de efficiëntie wordt verminderd.

Parkeerbeheer: strategieën voor SAV

Dit proefschrift draagt bij aan de verkenning van potentiële kansen en bedreigingen die voortvloeien uit de introductie van zelfrijdende voertuigen in onze steden, en welke acties planningsautoriteiten navenant zouden kunnen ondernemen. In het bijzonder wordt de impact van parkeerbeheer op de service-efficiëntie, de externaliteiten en de rechtvaardigheid van de dienstverlening gekwantificeerd voor een reeks scenario's, die opnieuw worden getest door middel van een agent-based simulatiemodel. De bevindingen suggereren dat het in het algemeen ook gunstig is voor de transportautoriteiten om ervoor te zorgen dat stilstaande voertuigen zo gelijkmatig mogelijk over het netwerk worden verspreid. Dit kan de gemiddelde wachttijden voor passagiers verminderen, maar ook de rechtvaardigheid van de dienstverlening vergroten, minder file veroorzaken en leiden tot een gelijkmatiger gebruik van de toegekende parkeerfaciliteiten. De extra voertuigkilometers, die worden afgelegd door deze verplaatsingsstrategie, dragen echter bij aan meer ongewenste externaliteiten. Een manier om voertuigen door parkeerbeheer gelijkmatiger over de stad te verspreiden, is door het aantal parkeerplaatsen per voertuig te verminderen. De resultaten van de simulatiestudies tonen aan dat het verminderen van het aantal van toegekende parkeerplaatsen de kwaliteit van de service nog meer kan verbeteren dan het vergroten van de vloot.

Conclusie

Zelfrijdende voertuigen kunnen de operatie van openbaarvervoersdiensten op een flexibelere manier betaalbaarder maken. Door de introductie van gedeelde geautomatiseerde voertuigen zou een vloot van kleinere voertuigen kunnen worden bediend, die on-demand transportdiensten aanbieden. Dit kan mogelijk van invloed zijn op de manier waarop we openbaarvervoersdiensten gebruiken en exploiteren, wat uiteindelijk veranderingen in het autobezit of landgebruik kan veroorzaken. Zulke veranderingen kunnen een unieke kans zijn voor transportautoriteiten en gemeenten om het transportaanbod en -netwerken, evenals de stedelijke ruimte, te reorganiseren, als ze een actieve rol spelen bij de introductie van zelfrijdende voertuigen. In dit proefschrift wordt aangetoond dat parkeren een belangrijke parameter kan zijn in dit proces. Parkeertarieven en parkeertijd kunnen de vervoersmiddelkeuze beïnvloeden. Verplaatsing van inactieve voertuigen heeft invloed op de service-efficiëntie, service externaliteiten en de rechtvaardigheid van de dienstverlening. Tot slot blijkt parkeerbeleid een effectieve manier te zijn voor transportautoriteiten om zelfrijdende voertuigen te reguleren.

About the Author

Biography

Konstanze Winter was born in Munich, Germany, in 1988. Before starting her studies, she worked as an au pair in France for one year. After a short detour via the Architectural Faculty, she obtained a bachelor's degree in Environmental Engineering from the Technical University of Munich in 2013. In 2015, she received the master's degree with distinction in Civil Engineering and Geosciences from Delft University of Technology. For a submission based on her master thesis "Development and Application of a Method to Design a Demand-Responsive Service Operated by Fully Automated Vehicles", she won the 2nd price in the category 'road' at the TRA Visions Young Researcher Competition. Throughout her studies, she received scholarships from the "Max Weber-Programm des Freistaats Bayern" and "Studienstiftung des Deutschen Volkes". Subsequently to her studies, she started as a doctoral candidate at the Department of Transport & Planning (Delft University of Technology) on a personal grant from the NWO TRAIL Graduate Programme. She was supervised by Oded Cats (TU Delft), Karel Martens (Technion – Israel Institute of Technology) and Bart van Arem (TU Delft). During her doctoral studies, Konstanze worked as a teaching assistant and supervised the thesis of a graduate student. She served as a reviewer for various international journals and conferences. Konstanze's research interests lie in the planning and management of urban traffic, shared mobility and the development of new forms of public transport. She is curious about the functionality of cities and how, in the long term, a sustainable way of living in urban agglomerations can be achieved.

Publications

Journal articles

- Winter, K., Cats, O., Correia, G. H. de A., & van Arem, B. (2016). Designing an Automated Demand-Responsive Transport System: Fleet Size and Performance Analysis for a Campus–Train Station Service. Transportation Research Record, 2542(1), 75–83. https://doi.org/10.3141/2542-09
- Winter, K., Cats, O., Correia, G., van Arem, B. (2018): Performance Analysis and Fleet Requirements of Automated Demand-Responsive Transport Systems as an Urban Public Transport Service. *International Journal of Transportation Science and Technology*, 7(2), 151-157.
- Winter, K.; Cats, O.; Martens, K.; van Arem, B.: Identifying User Classes for Shared and Automated Mobility Services. Under Review.
- Winter, K., Cats, O. Martens, K., van Arem, B.: Relocating Shared Automated Vehicles Under Parking Constraints: Assessing the Impact of Different Strategies for On-Street Parking. Under Review.
- Winter, K., Cats, O. Martens, K., van Arem, B.: Parking Space for Shared Automated Vehicles: Why Less Can Be More. Under Review.

Conference Contributions

- Winter, K., Cats, O., Correia, G., van Arem, B. (2015): *Designing a New Urban Mobility Service: Modelling Automated Demand-Responsive Transport System.* Presented at the Workshop on Smart Urban Mobility, November 2015, Edinburgh, United Kingdom
- Winter, K., Cats, O., Correia, G., van Arem, B. (2016): *Designing an Automated Demand-Responsive Transport System: Fleet Size and Performance Analysis for a Campus–Train Station Service.* Presented at the 95th Annual Meeting of the Transportation Research Board (TRB), January 2016, Washington, D.C., United States of America
- Winter, K., Cats, O., Martens, K., van Arem, B. (2017): *A Stated-Choice Experiment on Mode Choice in an Era of Free-Floating Carsharing and Shared Autonomous Vehicles.* Presented at the 96th Annual Meeting of the Transportation Research Board (TRB), January 2017, Washington, D.C., United States of America
- Winter, K., Cats, O., Martens, K., van Arem, B. (2017): *Impact of relocation strategies for a fleet of shared automated vehicles on service efficiency, effectiveness and externalities.* 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS), June 2017, Naples, Italy
- Winter, K., Cats, O., Martens, K., van Arem, B. (2018): *Relocating Strategies under Parking Constraints for a Fleet of Shared Automated Vehicles*. 7th Symposium of the European Association for Research in Transportation (hEART), September 2018, Athens, Greece
- Winter, K., Wien, J., Molin, E.J., Cats, O., Morsink, P., van Arem, B. (2019): *Taking The Automated Bus: A User Choice Experiment.* 6th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS), June 2019, Kraków, Poland

Data Sets

- Winter, M.K.E., Cats, O., Martens,K., van Arem, B. (2018): Stated Choice Experiment on Mode Choice in an Era of Free-Floating Carsharing and Shared Autonomous Vehicles: Raw Data. 4TU Centre for Research Data. Dataset. https://doi.org/10.4121/uuid:4ac4d7b7-c8b0-42ec-a096-55a4f1837585
- Winter, M.K.E., Narayan, J. (2019): Amsterdam Scenario MATSim. 4TU Centre for Research Data. Dataset. https://doi.org./10.4121/uuid:6108ed85-7b24-455e-bd95-89d84e6306fa

TRAIL Thesis Series

The following list contains the most recent dissertations in the TRAIL Thesis Series. For a complete overview of more than 250 titles see the TRAIL website: www.rsTRAIL.nl.
The TRAIL Thesis Series is a series of the Netherlands TRAIL Research School on transport, infrastructure and logistics.

Winter, M.K.E., *Providing Public Transport by Self-Driving Vehicles: User preferences, fleet operation, and parking management*, T2020/7, April 2020, TRAIL Thesis Series, the Netherlands

Mullakkal-Babu, F.A., *Modelling Safety Impacts of Automated Driving Systems in Multi-Lane Traffic*, T2020/6, March 2020, TRAIL Thesis Series, the Netherlands

Krishnakumari, P.K., *Multiscale Pattern Recognition of Transport Network Dynamics and its Applications: A bird's eye view on transport*, T2020/5, February 2020, TRAIL Thesis Series, the Netherlands

Wolbertus, R., *Evaluating Electric Vehicle Charging Infrastructure Policies*, T2020/4, February 2020, TRAIL Thesis Series, the Netherlands

Yap, M.D., *Measuring, Predicting and Controlling Disruption Impacts for Urban Public Transport*, T2020/3, February 2020, TRAIL Thesis Series, the Netherlands

Luo, D., *Data-driven Analysis and Modeling of Passenger Flows and Service Networks for Public Transport Systems*, T2020/2, February 2020, TRAIL Thesis Series, the Netherlands

Erp, P.B.C. van, *Relative Flow Data: New opportunities for traffic state estimation,* T2020/1, February 2020, TRAIL Thesis Series, the Netherlands

Zhu, Y., *Passenger-Oriented Timetable Rescheduling in Railway Disruption Management,* T2019/16, December 2019, TRAIL Thesis Series, the Netherlands

Chen, L., *Cooperative Multi-Vessel Systems for Waterborne Transport,* T2019/15, November 2019, TRAIL Thesis Series, the Netherlands

Kerkman, K.E., *Spatial Dependence in Travel Demand Models: Causes, implications, and solutions,* T2019/14, October 2019, TRAIL Thesis Series, the Netherlands

Liang, X., *Planning and Operation of Automated Taxi Systems,* T2019/13, September 2019, TRAIL Thesis Series, the Netherlands

Ton, D., *Unravelling Mode and Route Choice Behaviour of Active Mode Users,* T2019/12, September 2019, TRAIL Thesis Series, the Netherlands

Shu, Y., *Vessel Route Choice Model and Operational Model Based on Optimal Control,* T2019/11, September 2019, TRAIL Thesis Series, the Netherlands

Luan, X., *Traffic Management Optimization of Railway Networks*, T2019/10, July 2019, TRAIL Thesis Series, the Netherlands

Hu, Q., *Container Transport inside the Port Area and to the Hinterland,* T2019/9, July 2019, TRAIL Thesis Series, the Netherlands

Andani, I.G.A., *Toll Roads in Indonesia: transport system, accessibility, spatial and equity impacts,* T2019/8, June 2019, TRAIL Thesis Series, the Netherlands

Ma, W., *Sustainability of Deep Sea Mining Transport Plans,* T2019/7, June 2019, TRAIL Thesis Series, the Netherlands

Alemi, A., *Railway Wheel Defect Identification*, T2019/6, January 2019, TRAIL Thesis Series, the Netherlands

Liao, F., *Consumers, Business Models and Electric Vehicles,* T2019/5, May 2019, TRAIL Thesis Series, the Netherlands

Tamminga, G., *A Novel Design of the Transport Infrastructure for Traffic Simulation Models,* T2019/4, March 2019, TRAIL Thesis Series, the Netherlands

Lin, X., *Controlled Perishable Goods Logistics: Real-time coordination for fresher products,* T2019/3, January 2019, TRAIL Thesis Series, the Netherlands

Dafnomilis, I., *Green Bulk Terminals: A strategic level approach to solid biomass terminal design,* T2019/2, January 2019, TRAIL Thesis Series, the Netherlands

Feng, F., *Information Integration and Intelligent Control of Port Logistics System,* T2019/1, January 2019, TRAIL Thesis Series, the Netherlands