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Shared autonomous vehicle service design, modeling, and simulation

Reza Vosooghi

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Reza Vosooghi. Shared autonomous vehicle service design, modeling, and simulation. Mechanical engineering [physics.class-ph]. Université Paris Saclay (COmUE), 2019. English. NNT : 2019SACLC071 . tel-03166626

HAL Id: tel-03166626

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Shared Autonomous Vehicle Service Design, Modeling, and Simulation

Thèse de doctorat de l'Université Paris-Saclay
préparée à CentraleSupélec

École doctorale n°573 : INTERFACES : Approches Interdisciplinaires,
Fondements, Applications et Innovation
Spécialité de doctorat: Ingénierie des systèmes complexes

Thèse présentée et soutenue à Gif-sur-Yvette, le 28 Octobre 2019, par

Reza VOSOOGHI

Composition du Jury :

Dominique Barth Professeur, Laboratoire DAVID, Université de Versailles - St Quentin	Président
Kai Nagel Professeur, Technische Universität Berlin	Rapporteur
Dietmar Bauer Professeur, Universität Bielefeld	Rapporteur
Kara Kockelman Professeur, The University of Texas, Austin	Examineur
Fabien Leurent Professeur, Laboratoire LVMT, Ecole des ponts ParisTech	Examineur
Jakob Puchinger Professeur, Laboratoire LGI, Université Paris Saclay and IRT SystemX	Directeur de thèse
Marija Jankovic Professeur, Laboratoire LGI, Université Paris Saclay	Co-Directrice de thèse
Anthony Vouillon Team Leader, Groupe Renault-Nissan-Mitsubishi	Invité

To the brightest star in my life's sky

My daughter



Acknowledgements

First I would like to express my sincere thanks to the jury members of this PhD thesis: Prof. Kai Nagel from Technische Universität Berlin, Prof. Dietmar Bauer from Universität Bielefeld, and Prof. Kara Kockelman from the University of Texas, Austin, for accepting to review this work. Your reports were helpful in improving this manuscript, and rich in useful advice. I would also like to warmly thank Prof. Fabien Leurent from Ecole des ponts ParisTech, Prof. Dominique Barth from Université de Versailles - St Quentin, and Anthony Vouillon from Renault-Nissan-Mitsubishi for accepting to evaluate this work as examiners. It is a great honor to have my work assessed by you.

Second I would like to express my gratitude to my supervisors, Professor Jakob Puchinger and Professor Marija Jankovic for encouraging my research, good advices, cheerful mood and support whenever needed. I am also thankful for the revisions of both publications and thesis. I thank Göknur Sirin and Anthony Vouillon from Renault-Nissan-Mitsubishi for their help on data providing, and Frederic Da Silva from IRT SystemX for ensuring good conditions for my research in the MSM project.

Third I am grateful for conducting my research at IRT SystemX where I had the opportunity to meet many researchers and engineers specialized in different domains. I acknowledge the help and support from Dr. Feirouz Ksontini and Joseph Kamel on agent-based simulation. Many thanks to the Chair Anthropolise and Dr. Flore Vallet for the support and collaboration on research papers. I also would like to thank my friends particularly Dr. Ouail Al Maghraoui, Dr. Abood Mourad, and Dr. Danya Bachir for their friendship and emotional support through all these years.

Finally, I wish to express my love and my gratitude to my family for their constant support, encouragement, and never-ending patience. Special thanks to my wife, Alina, who has been extremely supportive of me throughout this entire process and has made countless sacrifices to help me get to this point.

Abstract

Shared autonomous vehicles (SAVs) are the next major evolution in urban mobility. This technology has attracted much interest of car manufacturers aiming at playing a role as transportation network companies (TNCs) and carsharing agencies in order to gain benefits per kilometer and per ride. An SAV service can merge cabs, carsharing, and ridesharing systems into a single transportation mode, and allow a more accessible, dynamic, and intelligent form of shared mobility. However, the success and competitiveness of future SAV services depend on their operational models, which are linked intrinsically to the service configuration and fleet specification. On the other hand, any changes in operational models of SAVs result in different demands for such a service in a real-world transportation network. Hence, considering the dynamic interaction of service and demand represents a key-factor for successfully designing SAVs in a real-life context. Using a comprehensive framework of SAV simulation in a multimodal dynamic-demand system with integrated SAV user taste variation, this thesis evaluates the performance of various non-electric and electric SAV fleets and their operational configuration, and to design the service. Overall, this thesis addresses several main research questions: What is the most appropriate approach to model the travel demand of SAVs and to simulate the service? Which metrics should be used to evaluate the performance of the service? What are the potential impacts of considering user taste variation on SAV service performance and configuration? Which SAV service configuration is more appropriate for both travelers and operators? If we consider a fleet of electric SAVs, how should the configuration of a relevant charging infrastructure look like?

To answer these questions, first, different approaches to SAV travel demand modeling and simulation techniques are reviewed and analyzed. Next, the required data and process, particularly synthetic population generation and activity chain allocation, are presented. In line with the purpose of this thesis, an overall framework of comprehensive SAV modeling and simulation is then proposed. Later, the results of a survey, conducted to explore the travelers' taste variation toward using driverless cars, are presented. The obtained results are used in the integration of user taste variation into the proposed modeling and simulation framework. Afterward, the impact of user taste variation on SAV service design and particularly fleet size is explored. Insights gained through a comprehensive investigation of SAV service performance considering fleet size, vehicle capacity, ridesharing and rebalancing, and service cost along with proposed key performance indicators are then provided. Finally, assuming a fleet of electric SAVs, the impacts of charging station placement, charging types (including normal and rapid charging, and battery swapping), variation in terms of the number of vehicles per charging outlets, and vehicle battery capacities, on service efficiency are explored.

This thesis is one of the first attempts to look at different fleet and infrastructure configurations of non-electric and electric SAVs in a realistic scenario. Although further efforts are required to improve the proposed framework of SAV service design, modeling, and simulation, the obtained findings highlight the significant importance of considering dynamic demand and heterogeneous user preferences in design and performance evaluation of such a new system.

Résumé

Les Robot-Taxis constituent la prochaine évolution majeure de la mobilité urbaine. Cette technologie intéresse certains constructeurs automobiles qui envisagent de jouer le rôle des entreprises de transport. Ceci leur permet de développer un modèle d'affaire basé sur des revenus par kilomètre parcouru et par trajet. Un service basé sur des véhicules autonomes a l'avantage de pouvoir fusionner des systèmes de service de taxis classiques à la demande et de voitures en libre-service. Ainsi ce service de transport unifié offre une forme de mobilité partagée plus accessible, dynamique et intelligente. Le succès et la compétitivité des futurs services de Robot-Taxis dépendent de leurs modèles opérationnels, qui sont intrinsèquement liés à la configuration du service et aux spécifications de la flotte. En utilisant une approche complète de modélisation et de simulation du service Robot-Taxi dans un système multimodal en valorisant la demande dynamique et la variation de préférences des voyageurs, cette thèse vise à évaluer les performances de diverses flottes de Robot-Taxi et leurs configurations opérationnelles. En général, cette thèse aborde les principales questions de recherche suivantes : Quelle est l'approche la plus appropriée pour modéliser la demande de déplacements des Robot-Taxis et simuler le service ? Quelles métriques faut-il utiliser pour évaluer les performances d'un tel service ? Quels sont les impacts potentiels de la prise en compte de la variation des préférences des voyageurs sur les performances et la configuration du service Robot-Taxi ? Quelle configuration de service Robot-Taxi est plus appropriée pour l'ensemble des voyageurs et des opérateurs ? Si nous considérons une flotte de véhicules autonomes électriques, à quoi devrait ressembler la configuration la plus adaptée d'une infrastructure de recharge ?

Pour répondre à ces questions, d'abord, différentes approches de la modélisation de la demande de déplacement de Robot-Taxi ainsi que des techniques de simulation sont passées en revue et analysées. Ensuite, les données et processus requis, en particulier la génération de la population synthétique et l'allocation de la chaîne d'activités, sont présentés. Conformément aux objectifs de cette thèse, un cadre général de modélisation et de simulation de services Robot-Taxi est ensuite proposé. Ensuite, l'impact de préférences des usagers sur la conception du service Robot-Taxi, et en particulier, sur le dimensionnement de la flotte est exploré. Des analyses approfondies des performances du service, considérant la taille de flotte, la capacité du véhicule, le partage de parcours et le repositionnement des véhicules, le coût du service, ainsi que les indicateurs de performance clés proposés, sont ensuite présentées. Enfin, en considérant une flotte de véhicules autonomes électriques (e-Robot-Taxi), l'impact du positionnement des stations de recharge, des types de bornes de recharge (y compris la charge normale et rapide), de la variation en termes de nombre de véhicules par borne de recharge, et de capacités de batterie du véhicule, sur l'efficacité du service sont explorés.

Quelques conclusions clés sont présentées ci-dessous :

- L'approche SMA (Système Multi-Agent) est l'approche la plus pertinente pour la modélisation des transports à la demande (TAD) et des services Robot-Taxi ;
- L'évaluation de la performance des services Robot-Taxi doit tenir compte de la demande dynamique de déplacement et d'un réseau multimodal ;
- Des préférences des usagers a un impact important sur la conception du service Robot-Taxi ;
- La performance du service Robot-Taxi est fortement corrélée avec la taille de la flotte ;

- Le repositionnement (réallocation) des Robot-Taxis impacte la performance du service ;
- La performance du service e-Robot-Taxi est corrélée avec la configuration de l'infrastructure de recharge et la capacité de la batterie ;
- La technologie « battery swapping » peut relativement améliorer l'accessibilité et l'efficacité du service e-Robot-Taxi ;
- La stratégie de positionnement des stations et bornes de recharge a un impact important sur la performance du service.

Le travail effectué dans le cadre de cette thèse est l'un des premiers essais pour examiner différentes configurations de flotte et d'infrastructure de Robot-Taxi, non électriques et électriques, dans un scénario réaliste. Bien que des efforts supplémentaires soient nécessaires pour améliorer le cadre proposé pour la conception, la modélisation et la simulation de services, les résultats obtenus mettent en évidence la prise en compte la demande dynamique et des préférences hétérogènes des voyageurs dans la conception et l'évaluation des performances de ce nouveau système de déplacement.

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List of acronyms and abbreviations

AMoD	Autonomous Mobility-on-Demand
AT	Autonomous Taxi
CAPEX	Capital Expenditure
CO	Combinatorial Optimization
DRS	Dynamic Ride-Sharing
DRT	Demand-Responsive Transport
DTA	Dynamic Traffic Assignment
FBS-MLC	Fitness-Based Synthesis with Multi-Level Control
FSM	Four Step Model
GTFS	General Transit Feed Specification
EV	Electric Vehicle
IPF	Iterative proportional fitting
IPU	Iterative proportional updating
LoS	Level of Service
OPEX	Operating Expenses
PT	Public Transport
PUMS	Public Use Microdata Sample
RP	Revealed Preferences
RTAC	Random Travel Activity Chaining
SAEV	Shared Autonomous Electric Vehicle
SAV	Shared Autonomous Vehicle
SP	Stated Preferences
TNC	Transportation Network Company
VoT	Value of Time

Chapter 1

General Introduction

1.1 Motivation and research context

Urban mobility has evolved significantly since the 1950s due to an important increase in car ownership and use, resulting in major road expansion and its infrastructure development. Undoubtedly, this evolution helped cities growing their economy and encouraged many people to settle in the urban and suburban areas. Over a few decades, urban areas have become increasingly automobile-dominated and major challenges such as air pollution and traffic congestion appeared (Newman and Kenworthy, 1998). Nowadays, planning and policies seek to reduce car use and to cut back on road provision, encouraging sustainable transportation, and promoting livable cities with a high quality of life (Newman and Kenworthy, 2015). Nevertheless, the use of motorized transport in urban areas continues to grow (e.g., in Paris greater area, Fig. 1.1). Even if the growth rate declined in the past decade, the increase in the use of private motorized modes shows that for most people these modes are still convenient enough compared to the other means of transportation in urban and suburban areas. In fact, even with very developed public transportation, the use of the private car will never completely disappear. This is particularly because of the intrinsic privileged accessibility and flexibility of private cars (Redman et al., 2013). Besides, private cars are very convenient for secondary trip purposes in urban areas (e.g., shopping and leisure), and they provide the best comfort compared to the public transportation services (Al-Maghraoui, 2019; Beirão and Sarsfield Cabral, 2007; Kent, 2015).

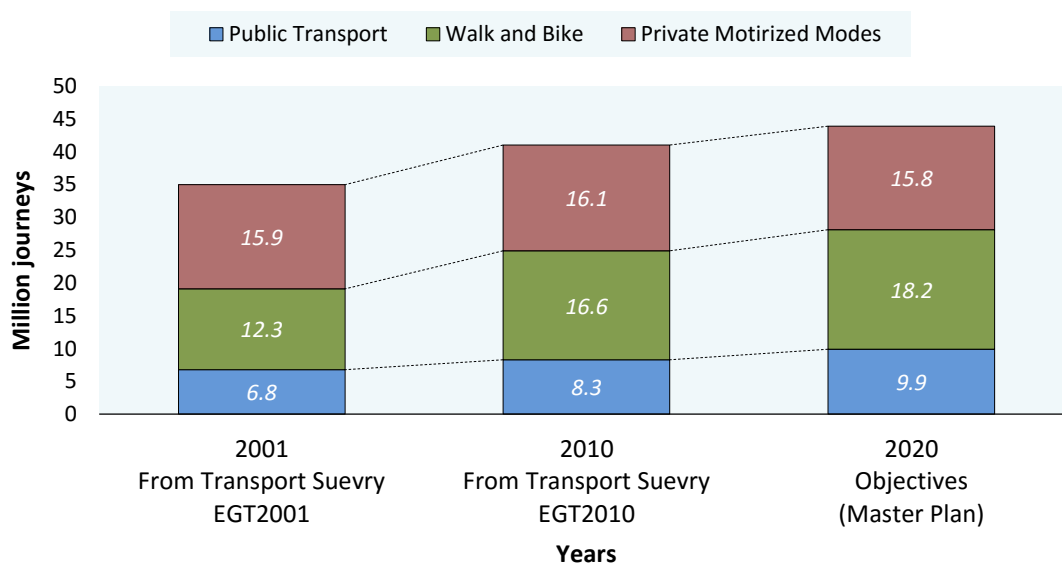


Fig. 1.1. Changes in the average daily transportation mode uses in Paris greater area

(Source: EGT-OMNIL¹, 2001 and 2010; PDUIF², 2020).

Today, private cars are an essential component of urban mobility that cannot be easily eliminated or neglected (Gärling and Schuitema, 2007). In recent decades, policymakers have focused on limiting private cars by increasing the cost of using and owning. Nowadays, the majority of policymakers in

¹ <http://www.omnil.fr/>

² <http://www.pduif.fr/>

particular in European countries do rather agree with the entire prohibition of private cars moving in some central or very dense districts. However, this kind of policies cannot be feasible for big regions; in the absence of appropriate alternatives, providing an affordable service of door-to-door for most of the trip purposes may not be properly guaranteed. In fact, to successfully achieve their goals by implementing limitation to private car users, policymakers should consider providing appropriate substitute solutions.

While significant efforts are made for decreasing car use in urban areas, the shared-use systems are becoming more popular. Especially in congested areas, the use of peer-to-peer ridesharing and ride-hailing services provided by Transportation Network Companies (TNCs), bike-sharing and electric-scooter sharing grows rapidly (Cohen and Shaheen, 2018; Conway et al., 2018). Travelers find their way to the destination within the shortest time avoiding congestion by using new shared-use transportation systems. Many others, who still prefer a car for their mobility in urban areas, have shown their willingness to use ride-hailing and ride-sharing services, avoiding worry about the availability of parking at the destination (Henao and Marshall, 2019). Due to technological advances of smartphones and universal internet access, shared mobility systems are becoming more flexible, accessible and affordable.

New shared mobility systems are highly attractive from an economic perspective. In the ride-hailing sector alone, more than \$13bn has been raised in 2018 for just two companies³: the ubiquitous Uber, and its rival firm in the United State and Canada: Lyft. This is why today big car manufacturers, such as Volkswagen, BMW, Daimler, and Renault-Nissan-Mitsubishi, are cooperating with transportation network companies to get involved in the sharing economy. Automotive companies are however still working on the making and selling of cars and developing related technologies. After having worked for several years on developing electric vehicles, they have succeeded in producing cheaper batteries (Nykqvist and Nilsson, 2015) and more models of battery electric vehicles come to market (Cano et al., 2018). Today, major automotive companies are working on autonomous-driving technologies. They have announced their plan to produce their first commercial autonomous vehicles (AVs) in the near future.

Given the increasing demand for shared mobility systems, and considering current technological advances in autonomous driving, it is very likely that future shared-use vehicles will be based on AVs. A system of shared autonomous vehicles (SAVs) could strongly reshape urban mobility. Within this system, a more flexible, accessible, and potentially even cheaper service than today's ride-sharing alternatives can be achieved (Litman, 2018; Meyer et al., 2017). Very similar to private cars, SAVs may be available within the shortest time and distance at any time of the day. Furthermore, using this mode, travelers experience a similar environment to conventional cars with an improvement in interior design that helps them to work or to do other activities during the journey. Travelers can also decide to share the ride and to pay even less for their trips. Within this system, travelers are less concerned about any changes in the quality of their rides that are often affected by human interactions. This is why SAVs are expected to revolutionize the riding experience.

The trend toward putting SAVs on the road is rapidly gaining momentum across a broad front that encompasses car manufacturers, mobility providers, technology companies, academic institutions, and

³ According to the financial statement of each company in 2018.

governments. Until now, it is not yet very clear how an appropriate and effective SAV service should look like. Car manufacturers and mobility providers are showing increased interest in the simulation of transportation network integrating SAVs and the design of the service realized by research institutions and academics. This thesis partially answers questions asked by Renault-Nissan-Mitsubishi alliance, aiming to market SAVs in the near future. This research is a part of the MSM project (Modélisation de Solutions de Mobilité), which was launched in June 2016 in IRT SystemX institute for a lifespan of 4 years and aims to provide new solutions that improve urban mobility. This thesis seeks to gain insights into the design of SAV systems considering vehicle specifications and the fleet's operational aspects. The traveler behavior with regard to using SAVs and the multimodality of the network are also considered during the simulation and modeling used in this thesis. These aspects are taken into account since the final goal is to apply SAVs in real-life transportation systems.

This thesis addresses more precisely the following research questions:

Research question 1: What are the simulation and modeling approaches to estimate the travel demand of SAVs and simulate the service? Which approach is the most appropriate for the goal of service design? What are the required data and processes?

Research question 2: What are the key indicators to evaluate the performance of SAV services?

Research question 3: What are the potential impacts of considering user taste variation on SAV service performance and configuration?

Research question 4: Which SAV service configuration is most appropriate for both travelers and operators? Which fleet size should one consider for a service of non-ridesharing or ridesharing SAVs? If the ride is shared, what vehicle capacity is most appropriate? Does the rebalancing have an important impact on SAV service performance?

Research question 5: By considering a fleet of electric SAVs, is the range of today's electric vehicles enough to satisfy an entire demand? If no, how should the configuration of a relevant charging infrastructure including charging location, type, and speed, look like? What are the impacts of vehicle battery capacity on the service performance?

1.2 Contributions

This thesis provides several contributions to research on SAV service design, modeling, and simulation. The main contributions are listed below.

- This is the first work that investigates the design of an SAV service in a multimodal network with dynamic demand considering heterogeneous user preferences. For this purpose, potential modeling and simulation frameworks are carefully reviewed and analyzed, and an appropriate framework is selected. To provide data on user taste variation required for the thesis purpose, a survey is designed and conducted. To the best of our knowledge, this is the first survey and travel analysis on AV and SAV use in France.
- This thesis is one of the first research studies that look at different fleet configurations of an SAV service in a realistic scenario considering both vehicle specifications and fleet configurations. In particular, single passenger SAVs and vehicles up to 6 passengers are investigated. A list of appropriate metrics is proposed to evaluate the performance of such a service. The analysis of given simulation outputs and interpretation of KPIs allow the

investigations on the effects of different operational components and vehicle specifications on the efficiency of the offered service. Furthermore, the analysis framework proposed in this thesis can support transport planners and service designers to align their evaluation metrics to the service stakeholders, providers and operators.

- This thesis investigates appropriate charging station configurations and vehicle battery capacities for a fleet of shared autonomous electric vehicles (SAEVs). New strategies of charging station placement are proposed and the impacts on SAEV service performance are assessed. Furthermore, the performance of service is evaluated according to the variation in the number of SAEVs per charging outlet unit. Until now, this evaluation has not been the subject of investigations. In addition, this thesis investigates for the first time the application of battery swapping stations (BSS) for SAEVs service.

It is important to note that this thesis considers only SAVs with the high or full automation levels (i.e., levels 4 and 5). Accordingly, conducted simulations and the survey do not take into account the transition period toward AVs. Also, it is important to underline that although the terms “self-driving”, “autonomous”, and “driverless” are often used interchangeably to describe a vehicle that can drive itself with zero human intervention, in this work for describing the simulated services only the term “autonomous” is used. Similarly, the term “SAV” is used to describe “Robo-Taxis”.

1.3 Thesis structure

Following this introduction, the remainder of this thesis is structured as follows.

Chapter 2 provides an overview of the state-of-the-art of SAV service modeling and simulation approaches. This chapter also analyses travel demand models and presents platforms employed for simulation of SAVs. Based upon the conducted analysis, an appropriate framework of simulation and modeling is proposed. Required data are presented and a general methodology for processing and preparing data is provided. Finally, the results of a survey that have been made during this thesis work to explore the user trust and willingness to use SAV service are presented.

In **Chapter 3**, the impact of user trust and willingness to use SAVs on fleet performance is explored. For this purpose, the survey presented in Chapter 2 is used. The main core of mode choice decision in the employed co-evolutionary algorithm is described, and further modifications for integrating user taste variation are presented. The details on estimated utility functions, synthetic population generation, and activity chain allocation for the case study area (Rouen Normandie Metropolitan area in France) are provided. The investigation presented in Chapter 3 is carried out assuming a fleet of non-ridesharing SAVs with a fixed monthly cost rate (unlimited rides); the vehicles are assumed without any range limitation. These assumptions are for considering only the impact of user taste variation on service performance.

Chapter 4 provides insights gained through a comprehensive investigation of SAV service performance considering fleet size, vehicle capacity, ridesharing and rebalancing, and service cost along with proposed key performance indicators. In this chapter, the assumed prices for SAV service are considered per traveled kilometer, thus presenting a different service than that considered in Chapter 3. Chapter 4 shows that taking into account the estimated average driven distance of SAVs, vehicle ranges, and possibly charging infrastructure need to be investigated in the next steps.

Chapter 5 assesses the impact of charging infrastructure and battery capacity on electric SAV (SAEV) service performance. Particularly, three strategies of charging station placement, two charging types (i.e., normal and rapid charging), different numbers of charging units in each station, and two different battery capacities along with battery swapping stations are assumed.

Table 1.1 summarizes the overview of the thesis and the main context of each chapter and specific research questions addressed in the corresponding chapters.

Table 1.1
Overview of the thesis.

Chapter	Main context	Research question				
		1	2	3	4	5
2	SAV simulation and modeling framework	√	-	-	-	-
3	Assessing the impact of user taste variation	√	√	√	√	-
4	SAV service design	-	√	√	√	√
5	SAEV and charging infrastructure	-	√	-	-	√

Chapter 6 summarizes key findings and insights of this research, highlights main limitations encountered when modeling and simulating SAV services, and suggests potential directions for future research.

All simulations, survey, data, population generation, activity chain allocation, and assumptions on the vehicle and infrastructure are based upon a real-world case study and inspired by ongoing experimentation of on-demand SAVs in Rouen Normandie Metropolitan area in France. Chapter 3, Chapter 4, and Chapter 5 are organized with a brief introduction of each component in the overall framework and the process of preparing the required data helping readers to read relevant subject while maintaining the overall view of modeling and simulation process.

The chapters are based on, or inspired by the following papers:

- Chapter 2: Vosooghi R, Puchinger J, Jankovic M, Sirin G. A critical analysis of travel demand estimation for new one-way carsharing systems. *IEEE 20th International Conference on Intelligent Transportation Systems (ITSC) proceeding (2018)*.
<https://doi.org/10.1109/ITSC.2017.8317917>
- Chapter 3: Vosooghi R, Kamel J, Puchinger J, Leblond V, Jankovic M. Robo-Taxi service fleet sizing: assessing the impact of user trust and willingness to use. *Transportation (2019)*.
<https://doi.org/10.1007/s11116-019-10013-x>
- Chapter 4: Vosooghi R, Puchinger J, Jankovic M, Vouillon A. Shared Autonomous Vehicle Simulation and Service Design. *Transportation Research Part C: Emerging Technologies (2019)*. 107, 15–33.
<https://doi.org/10.1016/J.TRC.2019.08.006>
- Chapter 5: Vosooghi R, Puchinger J, Bischoff J, Jankovic M, Vouillon A. Shared Autonomous Electric Vehicle Service Performance: Assessing the Impact of Charging Infrastructure and Battery Capacity. Under revision for publication in *Transportation Research Part D: Transport and Environment (2019)*.

Chapter 2

Simulation and Modeling Framework

The potential deployment of SAVs along with the increasing demand for shared mobility services have attracted the attention of mobility service providers, transport network companies, vehicle manufacturers and the transportation research community. Thus, the demand for an appropriate modeling and simulation framework of SAV services is increasing. This chapter provides an overview of the state-of-the-art of SAV service modeling and simulation approaches. After analyzing these approaches, challenges faced within the most popular approach, i.e., the activity/tour-based multi-agent simulation, are presented. The required data and process to perform such a simulation are discussed and an overall framework of SAV modeling and simulation is proposed. Finally, the results of a survey made for exploring the traveler taste variation toward using SAVs service are presented.

2.1 Introduction

In the last few years, the growth of service-oriented transport systems has favored the shift in private mobility from ownership to service use. Carsharing, a concept introduced for the first time in Switzerland in the middle of the 20th century and gained worldwide popularity in the 1990s (Shaheen and Cohen, 2007), is one of the first concepts of such systems. Developing the strategies and technologies for enabling users to gain short-term access to any other conventional private modes, such as bicycles and scooters, has resulted in a gradual increase in the popularity of shared mobility systems in the last decade (Shaheen et al., 2016). Nowadays, car manufacturers are also directly involved in vehicle-sharing operations (e.g., BMW with DriveNow⁴ or Renault Nissan with Moov'in Paris⁵) with the aim to find new channels to market the produced cars and to gain the financial benefits of new car-rental service systems (Firnorn and Müller, 2012). Technologies, such as smartphones, social network apps, the Internet, electric vehicles, keyless vehicle access, and in-vehicle and mobile global positioning system (GPS), receivers have played a major role in the growth of shared mobility systems over time. Due to the rapid developments of technologies related to AVs, the next revolution in the shared mobility systems is expected to be based upon these cars.

SAVs have the potential to take over a significant amount of traffic handled nowadays by conventionally driven vehicles (Fagnant and Kockelman, 2015; Soteropoulos et al., 2019). This new mobility system shares some similarities with the conventional or application-based cabs: both systems are on-demand and include empty pick-up rides for going and looking for the travelers. Compared to the conventional carsharing systems, SAVs have the capability to travel unoccupied to a waiting traveler, thus obviating the need for continuing the rental while at their destination. By anticipating future demand, SAVs could be autonomously relocated in advance to better match vehicle supply and travel demand at any time of the day. The accessibility and flexibility of SAV services make them more convenient than conventional small-size shared systems, such as ride-hailing, and station-based and free-floating carsharing. Given these advantages, the service based on SAVs could potentially merge cabs, carsharing, and ridesharing systems into a single transportation mode that is able to respond to a wide range of needs in urban mobility. SAVs are actually considered to have a transformative impact on many cities by enhancing transportation accessibility (Litman, 2018; Meyer et al., 2017), increasing multimodality (Moorthy et al., 2017; Ohnemus and Perl, 2016), changing vehicle ownership rate (Menon et al., 2019), and most probably reducing gas emissions (Bauer et al., 2018; Greenblatt and Saxena, 2015)⁶. However, like any other new transportation systems, the success and effectiveness of an SAV service will depend strongly on its operational configuration and the level of services that it provides for the travelers. To predict the potential impacts of SAVs on the transportation system and traveler behavior; and to appropriately design the service before placing it in operation, it is important to simulate SAVs and to estimate the eventual travel demand. This is usually done by travel models. Travel models produce quantitative information about travel demand and transportation system performance that can be used to evaluate alternatives and make informed decisions. The aim of this chapter is to give a holistic view of the existing methods of SAV service modeling and simulation, and travel demand estimation. The appropriate simulation platforms to model future SAVs integrated into multimodal systems in the form of on-demand transportation service are also identified and presented.

⁴ <https://www.drive-now.com>

⁵ <https://www.moovin.paris>

⁶ There are also many other references, especially on the impacts of AVs in general context. A review is presented in Milakis et al. (2017).

Moreover, it is illustrated why and how activity/tour-based multi-agent simulations are often used to estimate travel demand and simulate such a system and which limitations they have. The required data, and particularly synthetic population and activity chain analysis, are briefly reviewed and new approaches for preparing data are proposed.

The remainder of this chapter is organized as follows. Section 2.2 reviews the relevant literature concerning different approaches of SAV simulation and modeling. Section 2.3 provides a more in-depth analysis of those approaches and a presentation of employed simulation platforms. Section 2.4 describes the data required for the simulation of SAVs and particularly the essential data to employ activity/tour-based multi-agent approaches. Section 2.5 demonstrates the choice of the modeling approach and simulation platform, as well as a brief introduction of data preparation methods. Section 2.6 presents a conducted survey on SAV user trust and willingness to use along with a brief analysis. Finally, Section 2.7 provides insights gained through this chapter and introduces the next steps.

2.2 Prior research

To date, numerous investigations have been conducted on SAV modeling and simulation. Through consideration of three main components of a comprehensive SAV modeling and simulation framework (i.e., travel demand, network traffic, and service operation) and depending on the particular questions being addressed, these studies employ a combination of different approaches: (i) static or dynamic demand estimation, (ii) static, time-varying or dynamic traffic, and (iii) predetermined service configuration or optimization models. In the following, some general observations in this regard are presented:

- Static demand is widely used for various study purposes and particularly those related to the supply side of SAV services in operational research.
- Investigations relying on a static representation of the traffic environment rather incorporate static demand.
- Simulations based on the dynamic-demand approach involve two different multidimensional decision processes: (i) discrete choice modeling and (ii) utility scoring.
- In few dynamic-demand simulations, trip-based models are employed; thus, only main daily trips are simulated.
- Tour-based or activity-based demand models coupled with multi-agent simulations are the most recent approaches of SAV modeling and simulation.

Fig. 2.1 illustrates the components and alternative approaches for SAV modeling and simulation. A detailed list of previous studies stating modeling and simulation framework is presented in the following. It should be noted that because of the large number of research studies on SAV simulation, only those that focus on at least two components (demand estimation/ traffic simulation/ service configuration) are reviewed.

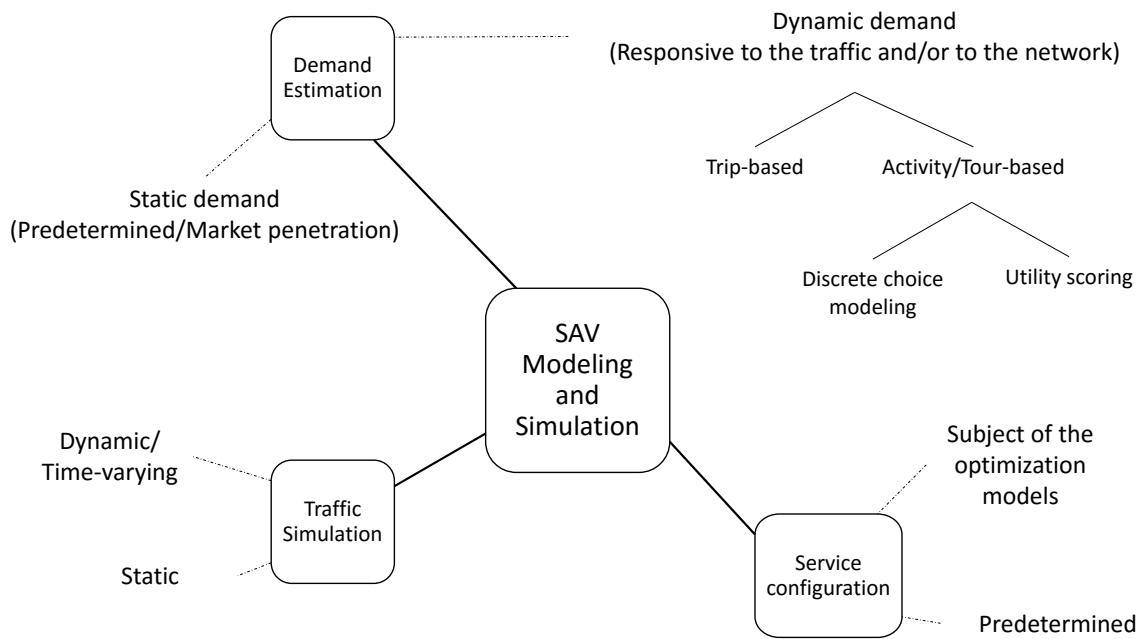


Fig. 2.1. Components and approach alternatives to SAV modeling and simulation.

In one of the first studies, Fagnant and Kockelman (2014) investigated the travel and environmental implications of SAVs and designed an agent-based model. The authors used predetermined demands that were generated for an interval of 5 minutes. Traffic congestion in this study is considered as a time-varying parameter. In order to operate SAVs, four relocation strategies with the aim of minimizing waiting times for upcoming request were used. While this research incorporates detailed models in the supply side of SAV service, the authors concluded that the heterogeneity in trip patterns, the integration of a mode choice mechanism, and the presence of a more realistic (congestible) network would be the next steps in improving their model. The same authors in a more recent study simulated a system of SAVs in Austin (Texas) with ridesharing capabilities (Fagnant and Kockelman, 2018). The demand, similar to the previous study, is considered static (market penetration); and this study aims at determining the optimal fleet size. The trips considered in their simulation represent 1.3% of trips taken in the case study region. Even if both of the mentioned studies do not incorporate dynamic and realistic demand, they are the pioneer studies investigating the SAV service and its analysis using relevant transport and service-related metrics. There are other studies that use or extend the same dynamic ride-sharing (DRS) algorithm proposed by the abovementioned authors; e.g., Zhang et al. (2015a).

Azevedo et al. (2016) used an integrated agent-based traffic simulator (SimMobility - Adnan et al. (2016)) built on disaggregated behavior models in both demand and supply to study the potential impacts of introducing of autonomous mobility-on-demand (AMoD) service in a car-restricted zone of Singapore. This study is based upon activity-based trips and discrete mode choice models. The employed supply simulator follows the dynamic traffic assignment (DTA) paradigm. This simulation was performed through some optimization processes in terms of facility location, vehicle assignment and routing, and vehicle rebalancing. This research is one of the first studies that incorporate sophisticated models in all components of SAV modeling and simulation, and includes a realistic scenario of an AMoD service.

Heilig et al. (2017) employed a multi-agent travel demand model, called *mobiTopp* (Mallig et al., 2013), using macroscopic traffic simulation in order to evaluate the transportation system of the Stuttgart region, where all the private cars are assumed to be replaced by an AMoD service. They performed simulation for more than one day (one week) and analyzed the changes in overall transportation system performance. The simulation encompasses the relocation strategy during nighttime. The demand is considered dynamic and based on activity and trip pattern of travelers. A discrete mode choice model is integrated into the simulation.

Boesch et al. (2016) used another agent-based simulation (*MATSim* - Horni et al. (2016)) to investigate the required SAV fleet sizes to serve different levels of demand (predetermined) in greater Zurich region in Switzerland. They used a demand pattern for private vehicles generated with *MATSim*, consisting of 1.3 million private vehicle users. The dynamic traffic simulation is integrated into the simulation. However, no network routing for SAVs in this study is incorporated. The static representation of travel demand and the lack of rebalancing in the supply side are the other limitations of this study. The main author of this study and others, performed a cost-based analysis of a SAV service and employed the same simulation framework with predefined demand and an integrated relocation strategy in a more recent research (Bösch et al., 2018).

Bischoff and Maciejewski (2016) employed *MATSim* to simulate the citywide replacement of private cars with various fleet sizes of Autonomous Taxis (AT) in Berlin. Although they simulated only one mode, this work provides one of the first insights in SAV dispatching in a dynamic demand simulation. The traffic simulation, as in other *MATSim*-based studies is considered dynamic.

Hörl (2017) made an effort to integrate AT service into the same simulation platform. The proposed simulation incorporated a pricing structure and a dispatcher, and simulated SAV service across Sioux Falls. The traffic simulation was considered dynamic. However, no further detail on the supply side of the SAV service is provided. Only one mode is simulated; thus, the multimodality in the network is ignored. The same author and others, tried to integrate discrete choice models into the co-evolutionary algorithm embedded in *MATSim* (Hörl et al., 2018). Also, they compared different SAV dispatching and rebalancing algorithms using the same simulation platform (Hörl et al., 2019).

Liu et al. (2017) simulated an SAV service integrated into the road network of Austin using *MATSim*, its utility scoring, and traffic simulation. In this study, the simulation was performed considering a multimodal network. The impacts of SAVs on energy use and emissions were investigated as well. Different SAV service fares and fleet sizes are assumed and different types of KPIs are interpreted.

Gurumurthy et al. (2019) used the same simulation platform to simulate travel patterns in Austin, and to assess the benefits of DRS with an SAV system. This work is based on a previous study aimed to investigate different strategies of congestion pricing and its impacts on the travel behavior, and network with high market penetrations of AVs and SAVs (Simoni et al., 2019). In both studies, the traffic simulation extension of *MATSim*, which is dynamic, and activity patterns of travelers are employed.

Wen et al. (2018) developed an agent-based platform in order to assess the dynamic interaction of travelers and a transportation system consisting of SAVs, integrated into public transport. The employed modeling framework incorporates a discrete choice model of the trip-based demand. Although this study provides some new insights into the design of SAV service in the context of a transit-oriented transportation system, it uses static travel times rather than time-varying or congested network.

Martinez and Viegas (2017) have applied another agent-based model in order to assess the impacts of deploying an SAV service in Lisbon, Portugal. The simulation incorporates trip-based travel demand and a discrete choice model. Due to the employed trip-based approach, demand estimation, vehicle allocation, and public transport assignment are performed in a spatially and temporal aggregated level. Several optimization models have been integrated into the model to assign dynamically the vehicles or generate them if needed for a given day during the simulation.

Zhao and Kockelman (2018), using a transportation planning software (TransCAD⁷), employed a traditional trip-based “four-step” model for the Austin region, in order to anticipate the regional impacts of shared connected and automated vehicle travel. In this study, they used a discrete choice model and a multi-class dynamic traffic network. The trips were spatially aggregated, and the day simulation was split into four time periods. No information about SAV allocation was provided. The authors concluded that for the simulation of such modes, employing an activity-based and agent-based model is more beneficial.

Despite the mentioned studies on non-electric SAVs, few investigations assess the implementation of shared autonomous electric vehicles (SAEVs) and employ the same modeling and simulation approaches. For instance, Loeb et al. (2018) and Loeb and Kockelman (2019) applied a tour-based model coupled with MATSim to anticipate the required charging stations as well as their sizes and positions, assuming a fleet of SAEVs serving travelers across the Austin. The demand in these studies varies dynamically. No information was provided about mode choice decision mechanism, neither for ridesharing nor rebalancing strategies of SAEV simulation. However, since the main core of these studies is similar to Chen et al. (2016) and Boesch et al. (2016), it seems that employed models take advantage of several optimization processes to find the best performing fleet or EV infrastructure.

Iacobucci et al. (2019) focused on optimization of SAEV operations based on the stochastic demand and simplified time-varying traffic upon the transportation network of Tokyo. This study is an extension of the work conducted by Zhang et al. (2016) that aimed to find optimal management strategies for rebalancing the SAV service. They reported that the demand in their simulation is dynamic; and only trips by car and taxi were simulated. Meanwhile, no information was provided about mode choice mechanism.

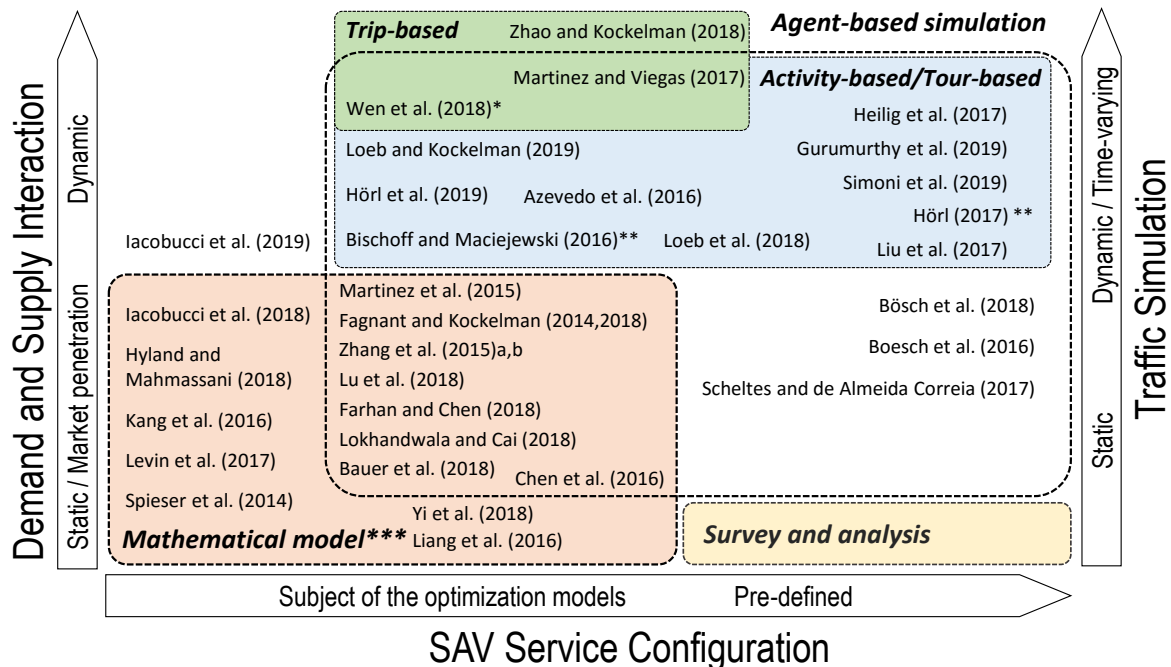
While in many other studies the SAV services are simulated, these studies focus only on one of the main components of comprehensive modeling and simulation. For instance, the SAV service as an alternative for last-mile trips, is investigated using agent-based simulation (Scheltes and de Almeida Correia, 2017) or by employing pure mathematical modeling (Liang et al., 2016). Some other investigations assess the impact of SAV service on urban parking demand (Zhang et al., 2015b), and the environment (Jones and Leibowicz, 2019; Lu et al., 2018). Transport models are also used to simulate SAEVs and design charging infrastructure (Bauer et al., 2018; Chen et al., 2016), and assess the impacts and potentials for transport and power grid integration (Iacobucci et al., 2018; Yi et al., 2018). SAV services are simulated in a mono-modal or multimodal network assessing various strategies on supply side of service, including vehicle assignment (Hyland and Mahmassani, 2018; Kang et al., 2016; Martinez et al., 2015), rebalancing (Babicheva et al., 2019), and ridesharing (Farhan and Chen, 2018; Levin et al., 2017; Lokhandwala and Cai, 2018; Spieser et al., 2014). In most of abovementioned studies,

⁷ <https://www.caliper.com/tcovu.htm>

demand estimation and traffic simulation are considered extremely simplified because of the already sophisticated optimization problems embedded in the simulation. In some other works, only one mode is simulated and no mode choice takes place. In addition to the abovementioned modeling and simulation approaches, there is a long list of studies in which survey and analysis methods are employed to produce rough estimations of potential SAV demand based on stated preferences (SP) surveys without incorporating any simulation (Bansal et al., 2016; Haboucha et al., 2017; Hao et al., 2019; Krueger et al., 2016).

Fig. 2.2 summarizes all reviewed studies by stating employed approaches of traffic simulation and travel demand modeling, and assumed service configuration. The key observations are as follows:

- In most studies, an agent-based simulation is employed.
- Studies based on mathematical models focus on the supply side of SAV service and ignore dynamic representation of demand and traffic network.
- Few studies incorporate dynamic traffic simulation with predefined demand and service configuration.
- Dynamic interaction of demand and supply in a congested network is considered in the limited studies.
- Most of the studies that assume dynamic demand are based on activity/tour-based travel demand model.
- All SAV simulations with activity/tour-based travel demand employ or are based on an agent-based simulation.



* In this study the traffic simulation is considered static.
 ** In these studies only one mode is simulated.
 *** Studies grouped in this category are not limited to presented list.

Fig. 2.2. An overview of studies that simulate SAV service by stating employed approaches on traffic simulation, travel demand modeling, and assumed service configuration.

2.3 Travel demand modeling and simulation approaches

2.3.1 SAV travel demand modeling

In the estimation of the travel demand for SAV systems, one can identify several approaches. In general, these approaches fall into three categories: (i) survey and analysis, (ii) trip-based discrete choice modeling, and (iii) tour-based/activity-based multi-agent simulation. It is important to note that the demand in the studies employing mathematical models is assumed predefined, random or varying according to the different levels of market penetration, and thus no travel demand estimation occurs.

Less precise methods of SAV demand estimation are based on **survey and analysis**. These methods are designed to produce rough estimations of potential demand by employing demand equations without incorporating traffic simulation. This approach has been originally developed for the cases with already existing data, thus it hinders the prediction when dealing with new innovative systems. Nevertheless, it is important to consider this approach because if coupled with regression or logit models they can be used for assessing user preferences (Gurumurthy and Kockelman, 2020; Haboucha et al., 2017; Krueger et al., 2016) and SAV adoption (Bansal and Kockelman, 2017; Lavieri et al., 2017; Quarles et al., 2019). Furthermore, within this approach, the impacts on SAV choice decision can be explored (Steck et al., 2018; Stoiber et al., 2019; Webb et al., 2019).

The second group of models is **trip-based travel demand** with discrete or simplified choice modeling. Trip-based models use the individual person trip as the fundamental unit of analysis. These models are widely used in practice to support regional, sub-regional, and project-level transportation analyses and decision-makings. Trip-based models are often referred to as “four-step” models (FSMs) because they commonly include four primary components: (i) trip generation, (ii) trip distribution, (iii) mode choice, and (iv) traffic assignment. FSMs are originally the dominant framework for operational transportation planning and policy analysis that have evolved over many decades. However, as the problems under study become more disaggregated, FSMs face several limitations. The fundamental weakness in this regard is that to model the SAV services, both spatial and temporal locations of vehicles are needed that aggregated FSMs cannot provide. Because of this requirement, all reviewed studies employing trip-based travel models, except Zhao and Kockelman (2018), have used an agent-based simulation as a disaggregated traffic simulator. Zhao and Kockelman (2018) emphasized this drawback of employed FSM and recommended using rather a multi-agent activity-based model for future works. In addition, because of this spatial aggregation due to the spatial zoning in traffic analysis, FSMs are not typically sensitive to short-distance trips. In an effort to reduce this limitation, Martinez and Viegas (2017) utilized extremely fine-grained spatial zoning (homogeneous grid of 200 m x 200 m cells) in their simulation. Some of the authors, mentioned in Fig. 2.2, also declared this weakness while simulating the carsharing systems with their models. For instance, Heilig et al. (2017b) point out in their simulation that access and egress trips to the carsharing are not modeled explicitly due to the zone-based spatial resolution. FSMs also do not consider the entire tours made by individuals and typically have high numbers of non-home-based trips, which do not include important information such as trip purpose or relation to other trips. Tour-based models partially address this limitation by adopting the tour (or trip-chain) as modeling unit. Tour-based models typically divide individual travel into home-based tours and non-home-based trips. As can be inferred, they still neglect linkages between trips forming part of non-home-based tours and linkages between different tours (Ortuzar and Willumsen, 2011). FSMs are

also essentially static as they represent travel over a particular time-period with a single state. Because of these weaknesses, they fail to adequately represent aspects such as the time of day chosen for travel (e.g., time-shifting in response to congestion or mobility pricing). For instance Zhao and Kockelman (2018), while splitting the simulation day into four time periods, used only the AM peak trip table for the assignment. Or, Martinez and Viegas (2017) stated that the trip time choice was kept unaltered in their model.

The third approach that is also the most popular one within reviewed studies is **activity/tour-based modeling**. Although the term “activity-based” is more used in the reviewed literature, in most of these studies it refers to tour trips or trip-chains since the activity and destination choice decisions are almost not enabled. In general, activity/tour-based models share some similarities to traditional FSMs: (i) activities performing within the study area are generated, (ii) destinations for the activities are identified, (iii) travel modes for trips connecting two activities are determined, and (iv) the specific network facilities or routes used for each trip are predicted. The explicit representation of realistic constraints of time and space and the linkages among activities and travels are the major advantages of activity/tour-based models over trip-based models. Activity/tour-based models also have the ability to incorporate very detailed person-level and household-level attributes in mode and activity choice mechanisms. They provide very detailed information about the user, service, and network-related metrics as output parameters (Castiglione et al., 2015). These capabilities are possible because activity-based models, in general, and some of the employed tour-based models, in particular, work at a disaggregate person-level rather than a simply aggregate zone-level like most trip-based models (Ortuzar and Willumsen, 2011). While this granularity is importantly appreciated in the modeling and simulation of the SAV service, only one study benefits those advantages of activity-based models related to the activity choice, particularly in long-term investigations (Azevedo et al., 2016).

2.3.2 *Activity-based/tour-based multi-agent simulation and platforms*

Agent-based simulations are among the most common and most recent approaches for the simulation of the SAVs. Reviewed multi-agent simulations have mainly roots in the activity/tour-based travel demand models. In employed activity/tour-based approaches, which incorporate detail information of trips and travelers, every individual is considered as a decision-maker who confronts a huge choice set of various activity and trip-chain patterns in the time-space domain. Each combination of activities and their locations, starting and ending points, activity durations (or activity end times), the mode chosen for moving from an activity location to another, and routes form a unique daily activity or trip-chain pattern. Individuals select modes, routes, and activities, or all of those together as patterns that maximize their utilities by somehow solving a large-scale combinatorial optimization problem conditional on others’ decisions, particularly on mode and route choices. Such disaggregate models require a computationally fast algorithm. Agent-based simulations, typically referring to a computational method and simulation for studying the actions and interactions of a set of autonomous entities (Zheng et al., 2013), provide an appropriate solution in this regard. This simulation approach becomes increasingly popular in AMoD research because of its advantages in capturing individual behaviors and enabling dynamic operations.

Apart from the simulation framework developed in each study separately, MATSim (Horni et al., 2016), SimMobility (Adnan et al., 2016), MobiTopp (Mallig et al., 2013), and POLARIS (Auld et al.,

2016) are the main activity/tour-based multi-agent platforms that have been used to model and simulate SAVs, carsharing, and on-demand services. Within most of the reviewed literature, MATSim is also used to provide details on traffic simulation.

MATSim is an open-source platform implemented in Java that is designed to run millions of agents. MATSim framework consists of several modules that can be combined or used stand-alone. Network simulation in this platform is queue-based (Horni et al., 2016). Currently, MATSim is considered as the most common simulation platform applied for new innovative transport services. All reviewed studies employing activity/tour-based multi-agent simulation, except Heilig et al. (2017) and Azevedo et al. (2016), used MATSim for the simulation. Loeb et al. (2018) and Loeb and Kockelman (2019) implemented MATSim to validate the tour patterns that they have modeled for Texas as well as for the dynamic traffic assignment. In other studies, MATSim was used only as a traffic simulator (Fagnant and Kockelman, 2018) or for estimating an initial demand (Boesch et al., 2016).

SimMobility is a simulation platform that integrates various mobility-sensitive behavioral models and considers land-use, transportation, and communication interactions. This simulation platform encompasses the modeling of millions of agents in mid-term to long-term perspectives and can include multimodal networks consisting of any conventional mode and the connectivity of those modes (Adnan et al., 2016). Similar to MATSim, this platform is designed to support the activity-based modeling paradigm, except that SimMobility incorporates more sophisticated and comprehensive land-use models. Hence, the range of possible decisions in the framework employed in SimMobility is broader; from travel (i.e., mode and route choice, and driving behavior) to land-use (i.e., household or firm location choice).

MobiTopp is another activity-based multi-agent platform that has been considered for an analysis period of one week when it was initially designed. This platform does not contain an internal traffic assignment procedure and mainly relies on external tools.

POLARIS is an open-source agent-based modeling framework designed for simulating large-scale transportation systems. Travel demand is estimated in POLARIS by using an activity-based demand model. The network model component in this platform is a one-shot simulation-based dynamic traffic assignment model. The major application of the POLARIS framework is the evaluation of ITS and management benefits.

All the above-mentioned platforms are declared as open-source. To date of writing this manuscript, only MATSim provides open access to the users.

2.3.3 *Challenges and limitations toward modeling and simulation of SAVs*

While the activity/tour-based multi-agent simulation of SAVs has many advantages over conventional transport models, some major challenges occur when employing such an approach. These challenges fall into three main categories: (i) data detail, accessibility, and reliability, (ii) high computational time, and (iii) calibration and validation.

The most important challenge in employing this approach is data. Activity/tour-based multi-agent simulation requires essentially very fine-grained data as input; and in particular a “synthetic population” and activities of each individual. In fact, in these simulations, to assign travelers to the right transport alternative, trips need to be modeled at the individual level with explicit modeling of the mode choice, which requires individual sociodemographic data. Likewise, in order to create a model sensitive to

short-distance trips (i.e., trips in which SAVs may be an interesting alternative for travelers), extremely fine-grained spatial information at the parcel level is needed. Not all these data are necessarily accessible and available. Accordingly, further efforts have to be made to generate and process the required input data. Moreover, as various types of SAV systems are not yet in operation, issue-specific SP surveys are needed, as well. Such surveys are costly and might not result in reliable and accurate models.

The second group of challenges is related to the computational effort. Theoretically, there are two major components of transportation models: (i) travel demand, represented by trip-chains or activity plans and (ii) traffic assignment, which estimates the traffic flows on the network. Traffic assignments are considered dynamic in all reviewed activity/tour-based simulations. The assignment outputs and mainly LoSs are used as inputs to the travel demand models. The big challenge for coupling these two components of modeling in the activity/tour-based simulation is that these models typically compute probabilities for a large number of alternatives at the individual level. To account for such alternative sets in assignment or simulation procedures for real size networks and a huge number of individuals would lead to very long computation times. Such a high CPU time is attributed to the fact that in most of the reviewed studies, the population of the study area is downscaled to small sizes; 0.1% (Loeb et al., 2018), 1% (Hörl, 2017; Hörl et al., 2019), 2% (Loeb and Kockelman, 2019), or 5% (Gurumurthy et al., 2019; Simoni et al., 2019).

Finally, there is an important challenge regarding calibration and validation of models. For any type of SAV services, there are no experience-based data at hand (as those services do not exist yet), so it is not obvious how to calibrate models according to the real behavior of travelers and validate whether these models run correctly. There is almost no validation process, presented or mentioned, in all reviewed studies - except for the base case scenarios, i.e., scenarios without SAVs.

2.4 Required data and process

As stated above, activity/tour-based models are more appropriate than FSMs to simulate SAV service in a multimodal network. The data required to develop and apply such a model are not significantly different from the data required to develop a trip-based model, but the important difference is that activity/tour-based models incorporate significantly more detailed input information and produce relatively more detailed outputs. By operating at the level of individual persons and households, particularly activity-based models use a wider range of important explanatory variables to predict travel patterns than trip-based models (Castiglione et al., 2015; Ortuzar and Willumsen, 2011).

The primary data used to develop both activity/tour-based and trip-based models include household travel survey information. Moreover, economic and demographic details about the spatial distribution of activities and households, and representations of transportation networks are required. Household travel surveys contain detailed information about whether, where, how, and when individuals and households travel. The same household surveys used to develop trip-based models can be used to develop activity/tour-based models, except that such surveys are subjected to much more scrutiny in developing an activity/tour-based model (Castiglione et al., 2015). For instance, Azevedo et al. (2016) used household interview travel survey (HITS) of Singapore or Loeb et al. (2018) and Loeb and Kockelman (2019) applied U.S. national household travel survey (NHTS). Activity/tour-based models, however, do require the development of two additional types of input: (i) a synthetic population, and (ii)

a fully descriptive daily activity plan or trip chains for every synthetic individual. Furthermore, to simulate an SAV service and to calibrate the travel demand model, additional data on user preferences and travel behavior toward this new alternative of transportation is required.

To achieve the most fine-grained modeling results (i.e., at an individual level), it is necessary to have input details of the individual or household characteristics, as well as main activity locations, for the entire population of the study area. Such data are typically collected in a population census. In general, it seems to be difficult to obtain such datasets for each individual person because they are expensive and normally protected by privacy laws. Thus, it is indispensable to find a solution to substitute population data in a synthetic manner. The purpose of population synthesis is to create a valid synthetic representation of the population in the study area that matches the distribution of individuals and household as per the demographics from survey and census data. In other words, a population generator or synthesizer produces detailed household or traveler characteristics that are consistent with known aggregate population or travel characteristics. Usually, the samples are obtained from public use microdata samples (PUMS) and the marginal data are obtained from the population census. While the synthetic population is an essential input for any activity/tour-based modeling of SAVs, the reviewed studies provide no details about methods and/or generators employed for the generation of the synthetic population.

Activity plans or trip-chains have to be also generated and associated with each synthetic individual. These data are often extracted from transport surveys, as in Azevedo et al. (2016), or travel demand models, as in Liu et al. (2017). It seems that there is enough information about trips and activity patterns of travelers for big American cities. Furthermore, since activity-based models are more popular in the United States, data preparation and particularly synthetic population generation are well documented, and some generators are developed and employed. Therefore, most of the mentioned studies on the US cities do not provide further information about the synthetic population generation and activity chain analysis.

In order to set up and calibrate the model and particularly mode choice mechanism, it is important to explore traveler tendency toward using future SAV. Despite several studies conducted on this topic within the last 5 years (Becker and Axhausen, 2017; Gkartzonikas and Gkritza, 2019), few efforts have been made for integrating user taste variations into SAV demand modeling and simulation. Chen and Kockelman (2016) employed a multinomial logit mode choice model in an agent-based simulation in order to investigate various dynamic pricing strategies on mode shares estimate of SAEV in Austin. In this study, the SAEV user preferences were assumed varied according to the traveler willingness to pay and value-of-travel-time (VoT). However, this study neglected user sociodemographic attributes in the SAEV mode choice mechanism. In Martinez and Viegas (2017), the sociodemographic attributes (i.e., age and income) are represented in the model by applying a discrete choice approach. As their model is based on real trip-taking activity (i.e., all modes currently available), sociodemographic attributes are neglected for SAV mode and some hypothetical variation in terms of car ownership and holding public transport pass are used instead. User taste variation toward using SAVs is neglected in all other studies mentioned in Fig. 2.2.

2.5 Proposed framework

As described in the introduction, this research aims at designing SAV services and to assess the impact of various configurations of vehicle, fleet, and infrastructure, on service performance and effectiveness. Within the reviewed studies and consistent with the analysis stated above, activity/tour-based models can potentially consider an appropriate granularity of data required to estimate demand and simulate SAV service in a multimodal context; and thus are more suitable for the goal of service design. However, choosing an activity/tour-based model involves certain constraints particularly in terms of required data. The synthetic population and the detailed activity patterns and trip-chains of the population across the region of the case study (Rouen Normandie Metropolitan area in France) are still lacking. In fact, in Europe, activity and tour-based models are not as popular as they are in the United States. In particular, until the date of writing this manuscript, activity-based models had not been developed or used to simulate the transportation system of any big region in France. Thus, population synthesis and activity chain analysis need to be initially performed to provide the required input for the simulation. A detailed description of proposed process on data preparation is provided in Chapter 3.

To implement travel demand modeling of SAV service and to simulate this new alternative in a multimodal network, a suitable multi-agent transport simulator is required. MATSim was chosen for the purpose of simulation. This choice is based on several reasons. First, this platform is open source and is widely employed within reviewed literature. Second, MATSim has extensive community involvement. The community provides assistance for the users and new developers. This also resulted in the availability of a large number of community-developed modules, which can be used and modified for the purposes of this work with a shorter time than developing a new module from scratch. Third, the flexibility of the co-evolutionary algorithm and particularly the scoring utility embedded in MATSim allow to integrate user taste variation. Based on the reviewed literature employing activity/tour-based multi-agent simulations, and consistent with the co-evolutionary algorithm of MATSim, the structure for the simulation and modeling framework is proposed as follows (Fig. 2.3).

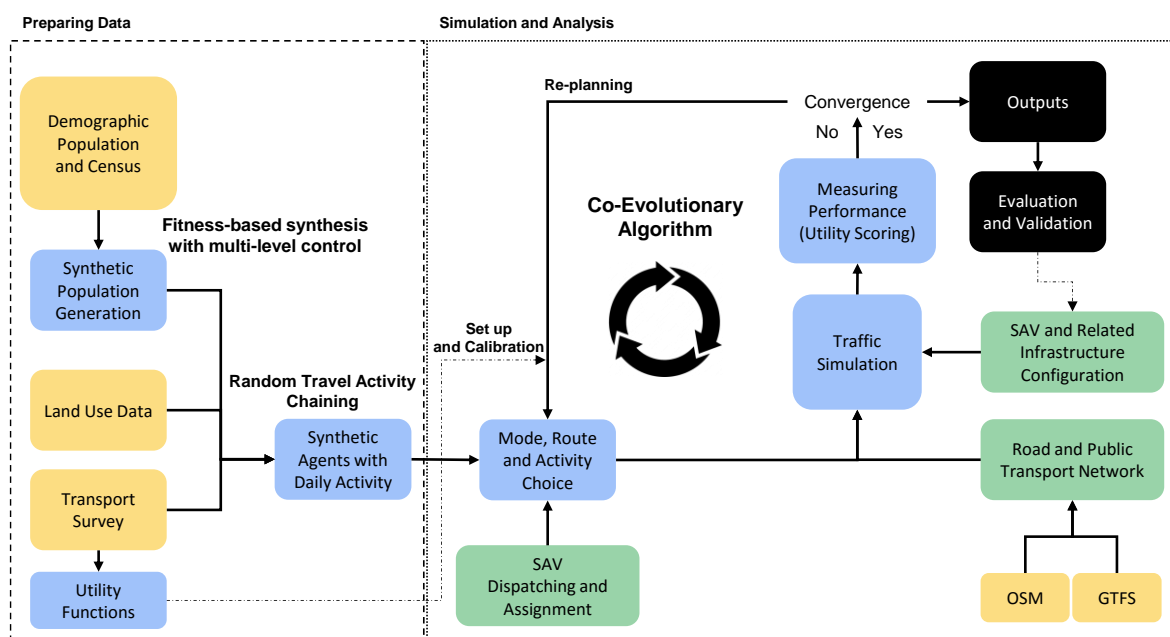


Fig. 2.3. The overall framework of SAV modeling and simulation.

First, a synthetic population is created from demographic data and census. To draw synthetic populations from samples, several methods have been found in the literature: (i) iterative proportional fitting (IPF), (ii) iterative proportional updating (IPU), (iii) combinatorial optimization (CO), and (iv) simulation-based synthesis. Based on the fourth method, a new simulation-based approach to generate the synthetic population of the case study area is proposed and developed. This approach is called “fitness-based synthesis with multi-level control” (FBS-MLC). The proposed methodology has some advantages over IPF/IPU and CO. First, simulation-based synthesis is more flexible in terms of adding additional attributes from other sources (Farooq et al., 2013). In particular, for the case study of this thesis work, household income attribute needs to be added, which is missing in the available PUMS in France. Second, while IPF and IPU require several data processing tasks to put data in a suitable format, simulation-based synthesis needs less effort and provides similar accurate outputs (Farooq et al., 2013). Finally, within the proposed method, the attributes that need to be more accurate can be chosen independently. It is worth mentioning that the microdata employed in this thesis consists of an acceptable sample rate (more than 35% of the whole population), which also helps to perform the simulation-based synthesis. More details on the generation of the synthetic population can be found in Chapter 3.

Second, trip-chains are extracted from the transport survey and activity plans are created using that survey, population census, and land use data. Usually, in the classic activity-based models, various activity sub-models are used to determine activity destination and choice. To develop these sub-models, very fine-grained data and particularly those related to the long-term predictions (in land-use and population demographics) are required. In addition, sophisticated discrete choice modeling should be processed to achieve accurate outputs. These models are not necessarily required for the simulation of this study. In fact, this research investigates the design of SAV services considering the actual trip patterns of travelers; thus, activity choice particularly due to the long-term evolutions and household decisions can be neglected. It is important to note that activity/tour-based multi-agent simulations and particularly MATSim adopt heuristic rules in feedbacks to achieve approximate convergence and consistency. Therefore, the activity chain and other characteristics of trips (known as the leg in MATSim) are modified or re-planned, and evaluated by utility scoring several times during the simulation in order to explore all potential alternatives that improve individuals’ trip and activity utilities. As a result, the sub-activity models are replaced by re-planning strategies in multi-agent simulations. Hence, to perform such a simulation, it is important to (i) determine the initial plans and (ii) calibrate the re-planning strategies. The activity plan comprises of activities’ location, its duration, start and end times, and the trips connecting two activities including mode and route (except initial plan). This thesis work proposes to allocate activity chains with specific individualized time periods to each synthetic agent according to the sociodemographic and socio-professional attributes along with the probability that have been found in transport survey. This process is called “random travel activity chaining (RTAC)”. A detailed description of the process is presented in Chapter 3.

Third, detailed road and public transport network are added into the simulation. The network data are extracted from OpenStreetMap (<https://www.openstreetmap.org>). The public transportation schedules and associated geographic information (GTFS) are obtained from the regional data provider. A program is developed to integrate GTFS data to the network and create a network file as a standard input of MATSim.

Fourth, the utility scoring of MATSim is set up according to the utility functions that are estimated for the case study area from a regional transport survey. The simulation is performed several times to calibrate the scoring utilities by comparing the observed and estimated modal splits and trip distances.

Finally, the simulation is set up according to the SAV service, its infrastructure configuration, and some operational details. Several modules already developed in MATSim are used and modified for this purpose. These modules are cited and related algorithms are briefly presented in each chapter depending on the particular simulation being performed within the purpose of chapter. For the simulation of electric SAVs, an external model is developed and applied to perform the charging station placement.

In the employed multi-agent platform, when the first iteration of the simulation is started, routes are assigned to each individual and the traffic simulation estimates the time variables. In following iterations, modes, routes and departing times are revised. The traffic simulation and mode choice process are performed in some other studies in a separate model. In MATSim, this process can be done during simulation using integrated modules.

The main process of decision mechanisms, particularly mode choice, is usually based on a discrete choice approach. This approach, in turn, relies on the assumption of random utility maximization. However, MATSim does not involve discrete choice models as they are typically used in transport demand models. The choice decision in this simulation platform is based on finding stochastically the maximized utility for various choices sets. The principal process is that every agent has the ability to learn and adapt its behaviors based on experience, which requires some form of memory. The discrete choice capability provides agents to select one plan from their memory. For this aim, a set of individual choices or plans is memorized and then they are examined during the plan executions. This process is called co-evolutionary algorithm (Horni et al., 2016).

A mesoscopic queue-based simulator handles the traffic simulation in MATSim to find network performance and LoS measures. A full day simulation according to the longest agents' plan is performed. The plans' score including trips (legs) and activities utilities are calculated for each individual. In the following "active" iterations, the plans are modified (re-planning). The simulation iterates several times so that each agent experiences different combinations of modes, routes, and depart times. The simulations end up with some "passive" iterations in which all choice decisions, except plan choice, are disabled and memorized plans are examined. The iteration process is repeated until average performance measures for all agents stabilize and a systematic relaxation is reached. Finally, the network, user, and service-related performance indicators are evaluated and analyzed using the specific KPIs that are presented later in next chapters. The simulation outputs are validated by comparing the results and trends with other similar investigations.

2.6 Survey on SAV user trust and willingness to use

As stated in Section 2.3, exploring travelers taste variation toward using SAVs and integrating it to the model is one of the main missing components in the comprehensive simulation and modeling of such a service within the reviewed studies. To avoid this limitation, a survey on SAVs user taste variations was made (Al-Maghraoui et al., 2019). The aim of this survey was to investigate the reasons behind travelers' acceptance and willingness to use future SAVs, depending on their explicit market segmentations. Although this survey addresses people who are living in another region (Paris greater area) rather than the case study area of this thesis (Rouen Normandie metropolitan, France), it reflects accurately the personal attributes of French travelers that affect the acceptance and using a driverless car. Undoubtedly, this survey is the first attempt to show the importance of considering SAVs user taste variation and can be completed and repeated addressing local users in the future research.

The following presentation of the survey, its results, and the conducted analysis were co-authored by Ouail Al-Maghraoui who explored traveler experience during his thesis at the time of conducting this survey (Al-Maghraoui et al., 2019; Al-Maghraoui, 2019).

The first part of the designed survey was organized into three blocks: (i) sociodemographic attributes (i.e., age, gender, socio-professional category, and income), (ii) typical daily one-way journeys including origin-destination regions, mode of transport, monthly cost, and travel-related times (depending on the mode: waiting time and the time for looking for a parking place), and (iii) evaluation of the current journey (on a 5-point Likert scale) in terms of safety, security, comfort, and freedom during travel. At the end of these blocks, participants were asked if they would rather use an AV instead of their current mode of transport (answer a priori). Employing the above information, an alternative trip using SAVs was simulated for the same participants' travel attributes. The cost was estimated from the prices of Lyft USD 300/30 rides subscription plan (Lyft, 2018). The total travel times were calculated using the total travel time given by the participants.

The second part of the survey exposes the simulated travel to participants and asks them if they would use the SAVs in the future as a replacement of their current mode of transport (a posteriori answer). Depending on their answer, they are asked to give a score (5-point Likert scale) to tell how important each of the criteria behind their decision is. The list of the criteria is generated depending on the mode (as for the second block of the first part of the survey, i.e., typical daily one-way journey). If participants' answer is "Yes", they are asked if they would pay an extra 20% to have a private ride as VIP travelers.

The survey had 457 participants. More than 50% of the participants were young people under 24 years old, of which most of them were men (67%). The socio-professional category distribution was composed mostly of "Active" and "Students" (94%) while the real proportion of "Active" categories of the Paris greater area was 88% (INSEE, 2018). The incomes were fairly distributed with a higher proportion (35%) of the [1 k€, 2 k€] segment. The trips outside Paris region were 87% of the total number of the whole region trips, while the real proportion was 70% (OMNIL, 2017).

The first part of the survey shows that 67% of participants would accept to use an AV as an alternative to their current mode of transport (Fig. 2.4). Car users had the largest potential to change their transport mode, followed by public transport users (60% conversion rate for car users and 58% for PT users). Travelers biking or walking did not score that high with 20% together. In the second part of the survey, after informing the participants of how the use of SAVs would be like for their current typical journey, it was found that 30% of them would use SAVs as a replacement of their current mode of transport. In the latter case, car users had the largest potential to change mode (27%), followed by public transport users (17%). Travelers that use biking or walking did not state that they would be ready to change their mode (8% together). Compared to the acceptance of AVs, the percentage of PT and car users who state their willingness to use SAV service decreased by 41% and 33%, respectively, where biking and walking only decreased by 12% each.

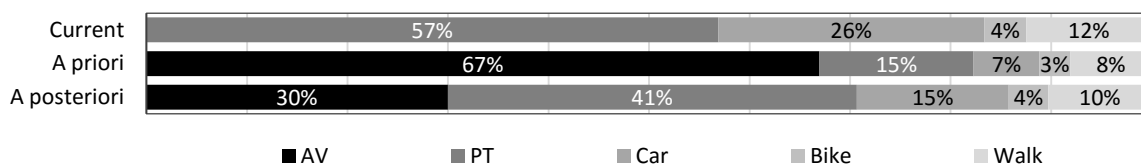


Fig. 2.4. AV acceptance rates vs. SAVs willingness to use regarding the current modal split of Paris greater area.

Fig. 2.5 illustrates the distributions of answers (Yes/No) in the first part of the survey through age, gender, socio-professional category, income, transport mode, and origin-destination regions. These represent the projection of the AV technology acceptance of participants. It appears that there are some differences between the categories of each segmentation, especially in mode, age, and gender. In the transport mode, for example, it is clear that biking and walking have lower rates of acceptance than PT and car. Moreover, consistent with findings in the literature (Bansal and Kockelman, 2018; Gurumurthy and Kockelman, 2020; Haboucha et al., 2017; Krueger et al., 2016; Simoni et al., 2019), seniors are more likely to not to accept AVs than young adults. However, since participants in each category are not equally represented, a regression tree is built to see which categories mostly influence AV acceptance (Fig. 2.6).

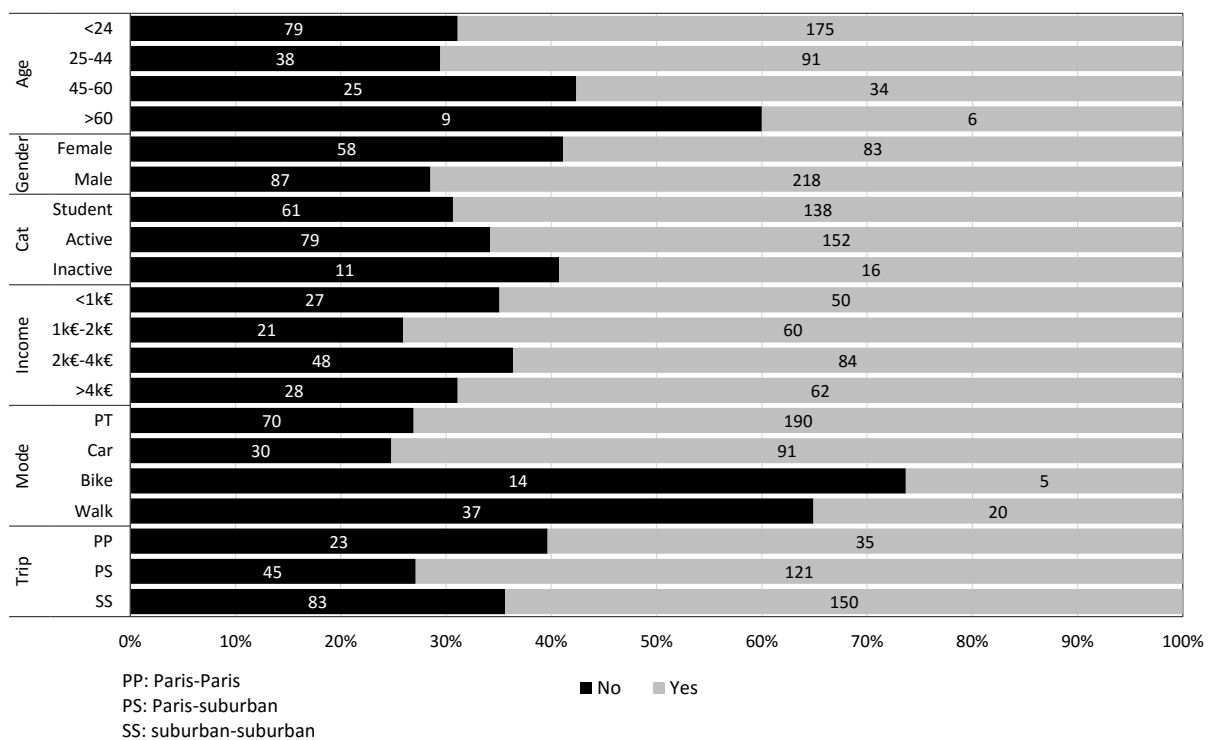


Fig. 2.5. Distributions of answers a priori by sociodemographic attributes.

According to Fig. 2.6, the four main influencing factors on AV acceptance are the current mode of transport, the gender, and the socio-demographic category along with the origin-destination geographic area. Among the 67% of all participants who responded Yes, 86% are PT or car users. Four profiles of participants that score higher than 70% of AV acceptance probability are identified and presented as follows. These groups of people represent together 56% of all participants who answered Yes; they are all PT or car users:

1. Male participants who are “Students” or “Inactive” (88% probability)
2. Male participants who are “Active” and earn more than 2 k€/month (80% probability)
3. Male participants who are “Active”, earn less than 2 k€/month, and own a car (74% probability)
4. Female participants who commute between suburbs (73% probability)

Participants with modes “bike” and “walk” are more likely to not to accept AVs with a probability of 59%. According to other comments of participants, the main reasons for such reluctance are that the short distance commute does worth it or that it is healthier to walk or cycle (Al-Maghraoui, 2019).

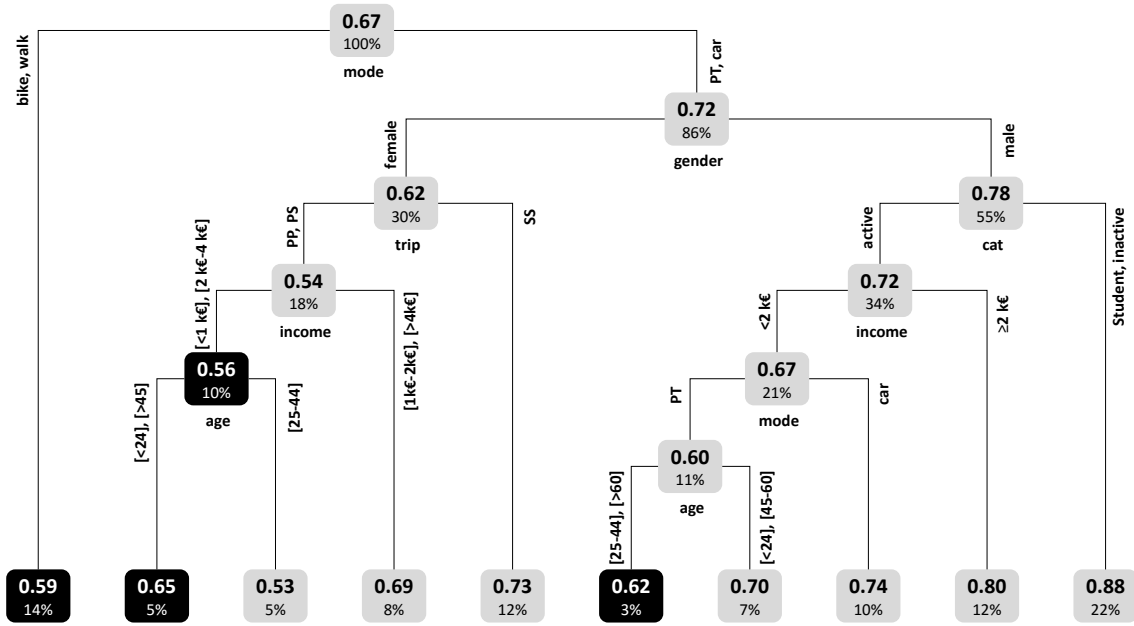


Fig. 2.6. A regression tree built to identify the main criteria behind respondents’ answers regarding AV acceptance.

Two other regression trees are generated to demonstrate the hierarchy of criteria of willingness or unwillingness to use SAVs (Fig. 2.7). Fig. 2.7a shows that regarding willingness to use, comfort is quite discriminating given the fact that people who give it a score of 5 have a probability of 80% to accept the use of SAVs. Travel time and freedom are less discriminating given their lower probabilities. For negative answers (Fig. 2.7b), the most influencing criteria on SAVs unwillingness to use are cost, security, and the current mode of transport. The most reluctant participants give higher importance to cost (≥ 3.8 average) with a probability of 97%. Meanwhile, those who do not use a car as a current mode (with a potentially small transport budget) have a probability of 84%. Finally, participants giving less importance to cost (> 2.8 average) and higher importance to security (≥ 4.7 average) have a probability of 78% of not using SAVs.

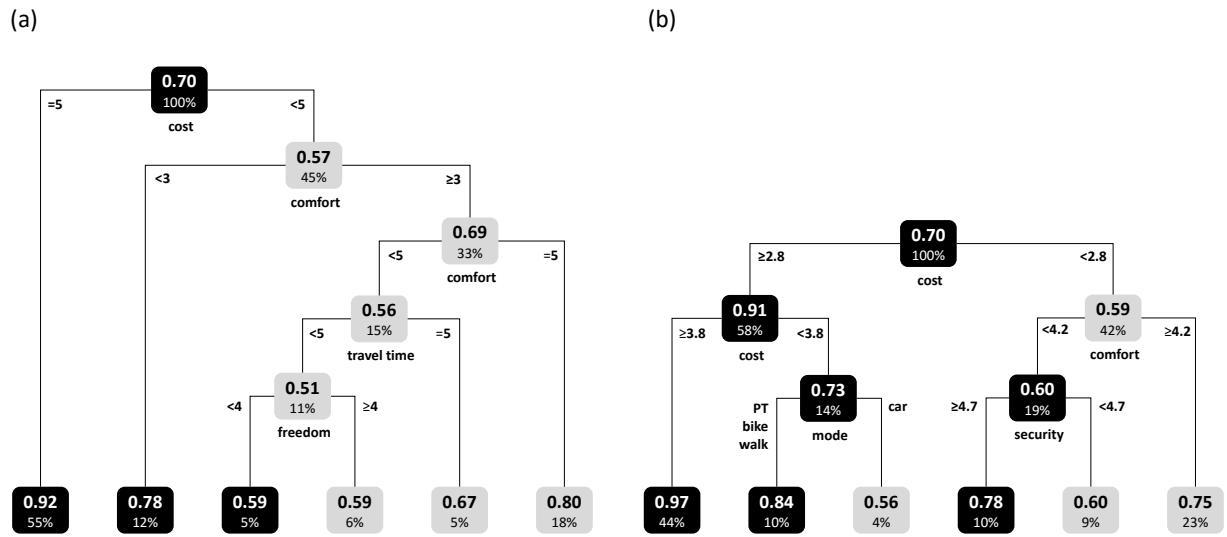


Fig. 2.7. Regression trees built to identify the main criteria behind respondents' answers regarding (a) willingness to use SAVs and (b) unwillingness to use SAVs.

The results suggest the presence of a correlation between travelers' specific attributes and their positions regarding driverless cars and SAVs. The answers of participants to the question if they would one day, "a priori", use an AV instead of their current mode of transport may be assumed to reflect the user trust. The answers to the question whether they would, "a posteriori", replace their current mode of transport by the SAVs may also be assumed to represent travelers' willingness to use the SAVs in the future. Thus, we propose to measure the user taste variation by travelers' sociodemographic and socio-professional attributes as well as their current mode of transportation. In Chapter 3, this variation is integrated into the model and an illustration of how it can affect the SAV service design, particularly fleet sizing, is provided.

2.7 Conclusion

This literature review emphasizes how travel demand models for SAVs are limited. In particular, when the complex relationship between supply (network and service) and demand are considered. Most of these investigations are based on activity/tour-based multi-agent simulations. Compared to the classic four-step models, the activity/tour-based approach is more appropriate for the travel demand modeling of SAVs. Particularly, the granularity of data required for the traffic simulation of SAVs and the need of decision process at an individual level for such a service have motivated transport planners and researchers to move to the activity/tour-based multi-agent simulations. Although the term "activity-based trips" refers rather to "trip-chains" in most of the reviewed studies, it almost covers the limitation of conventional tour-based models especially in terms of linkages between different tours. Agent-based simulations are mostly employed for the activity/tour-based modeling of SAV service since this simulation approach is fast enough to handle high number of decisions at the individual level and to estimate network LoSs at a fine level of details. Obviously, such a simulation requires very detailed data as input. This granularity of data provokes many efforts in the data preparation, particularly synthetic population generation and activity pattern or trip-chain analysis.

In order to design an SAV service employing comprehensive modeling and simulation, several components especially related to users and the configuration of the service are not yet taken into account. The user taste variation is almost neglected in all reviewed studies. With regard to this point, a survey addressing French travelers and its analysis showed that user trust and their willingness to use vary importantly within different groups of people categorized by their age, gender, households' income and the socio-professional profile. The observed variation reveals the importance of considering travelers sociodemographic and socio-professional attributes in SAV choice decision. Concerning the design of SAV service, most of the reviewed studies, especially those that focus on operational investigations, incorporate static demand or market penetrations. This static representation of SAV demand does not properly reflect the behavior of users in a multimodal network and affects certainly the service design.

Based on the performed analysis and presenting limitations in prior studies, and in line with the purpose of the present research study, the framework of SAV modeling and simulation is proposed. Some data preparation methods and processes for the simulation are also proposed and briefly presented. The next chapter involves investigations on how to integrate user taste variation into the proposed framework of activity/tour-based multi-agent simulation and exploring how this variation affects the SAV service design and particularly fleet size

Chapter 3

Assessing the Impact of User Taste Variation

The first commercial fleets of SAVs will be on the road soon. Today important efforts are made to anticipate future SAV services. Fleet size is one of the key parameters considered in the planning phase of service design and configuration. Based on multi-agent approaches, the fleet size can be explored using dynamic-demand simulations. Time and cost are the most common variables considered in such simulation approaches. However, personal taste variation can affect the demand and consequently the required fleet size. In this chapter, the impact of user trust and willingness to use on the SAV service performance and fleet size is explored.

3.1 Introduction

Technology advancements on autonomous driving as well as increasing popularity of recently appeared shared mobility and on-demand services show that personal mobility will profoundly change in the next decades. Travelers increasingly use such services because they become more accessible, easy to use and affordable (Chan and Shaheen, 2012; Shaheen et al., 2016, 1998). With the reference to past experiences, these advantages for users result in various issues for the operators (Shaheen et al., 2015). One example is fleet rebalancing. The emergence of AVs could result in resolving such issues. The idea may be to share a fleet of AVs, which is maintained and managed by a third-party organization, to respond to the travel demand of the entire urban population or a community. This shared mobility on-demand service is called in this thesis work “Shared Autonomous Vehicles (SAVs)”⁸. Such considerations are of high importance for car manufacturers given their recent investments in AV technology. Automakers are aware of such transformation and are interested in playing the role of an operator with new business models capturing profit per kilometer or per trip (Firnkorner and Müller, 2012; Stocker and Shaheen, 2018).

In order to design future SAV services, the basic operational characteristics are to be estimated in the upstream planning. Fleet size, fleet specifications, relocation strategies and service area are the main ones. Due to recently developed demand-responsive simulation and modeling, those characteristics and their impacts on service demand can be explored at a fine-grained level. The major part of recent studies on planning for future SAVs are focusing on this subject. For this purpose, agent-based simulation is widely applied. Compared to other approaches, due to the disaggregate temporal and spatial data in the simulation, complex supply-demand relationships can be assessed (see Chapter 1, and Vosooghi et al., 2017). Nevertheless, the application of such approaches is usually limited to the operational aspects of SAVs. One of the research gaps is that the traveler tendency to use such service is not integrated into the simulation as an influencing factor of the use of a driverless car. This chapter aims to fill this gap by providing a novel method in order to integrate both user trust and willingness to use into recently applied multi-agent simulation with the aim of exploring their impacts on SAV service fleet sizes. Furthermore, the waiting time as an essential factor of mode choice decision is incorporated into the simulation. To the best of our knowledge, this is the first time that individual systematic taste variation and service waiting time is considered in SAV fleet sizing simulations. It is important to note that in this research, the demand of a new service is assumed not to be eliminated due to the service acceptance but substituted by other modes (if available with less disutility). However, the importance of service acceptance could be as well explored with the proposed approach.

The main contribution presented in this chapter is the proposition of a new scoring process in a widely used multi-agent transport simulation platform, MATSim. A second contribution is synthetic population generation and activity chain analysis. Simulation experiments in this thesis are based upon the real data for the transportation system of the Rouen-Normandie metropolitan area in France. The survey described in Chapter 2 is used for the integration of user trust and their willingness to use future SAVs. The remainder of this chapter is structured as follows. First, Section 3.2 presents a review of the relevant

⁸ Other concepts of autonomous on-demand mobility systems, such as the sharing of a fleet of AVs among a group of members or company employees requiring a pre-subscription can also be developed. However, the term “SAVs” and “SAEVs” in this thesis refer only to Autonomous Taxi or Robo-Taxi systems.

literature. This is followed in Section 3.3 by the methodology description. Section 3.4 describes the data preparation and scenario setup. Section 3.5 describes detailed results and comparisons. Finally, Section 3.6 discusses insights gained through this chapter and provides suggestions for next steps.

3.2 Related work

A review of the existing literature reveals the large attention given today to behavioral experimental studies considering the use of various types of AVs. Some limited investigations also address the case of SAVs (Bansal et al., 2016; Haboucha et al., 2017; Krueger et al., 2016; Steck et al., 2018). In almost all these studies, the traveler perception and tendency toward using AVs are explored in an attempt to predict the market penetration rate. However, the results have not been taken into account in the comprehensive travel demand models. One of the main reasons is the fact that developing relevant models for on-demand and shared transport systems is still in progress. The most appropriate approach to simulate such systems is considered to be activity/tour-based multi-agent simulation (see Chapter 1). This approach is widely used today. Nevertheless, several components specifically related to the interactive relation of demand and transport service still need more investigation. Hörl (2017) has addressed this issue in the simulation of ATs and developed an extension of a previously-developed framework in order to make multi-agent simulation demand-responsive. Wang et al. (2018) also dealt with this issue and proposed a different methodology with the aim of exploring fleet size and strategy optimization of an autonomous on-demand service. Fagnant and Kockelman (2018) applied a more sophisticated approach for fleet sizing of a system of SAVs in Austin. All aforementioned studies are based on MATSim (Horni et al., 2016), and clearly none of them has integrated the traveler-related aspect of decision-making. We addressed the impact of user preferences on SAV modal share in Paris, applying a similar simulation approach (Kamel et al., 2019). In our work, traveler preferences have been integrated into the scoring function used within a co-evolutionary algorithm embedded in MATSim. For the case study scenario, all the taxis have been replaced by SAVs and the simulation results have been compared. The results reveal the significant difference of overall modal split of SAVs, as well as the use of this service, before and after the introduction of user preferences. In the mentioned study, SAV utility has been defined based on conventional taxi utility without considering the impact of waiting time. Martinez and Viegas (2017) have applied another agent-based model in order to deal with the discussed issue. In their study, the sociodemographic attributes (i.e., age and income) are represented in the model by applying a discrete choice approach. However, as their model is based on real trip-taking activity (i.e., all modes currently available), those attributes are neglected for SAV mode.

The impact of individual-related attributes on the mode choice is well reflected in the classic travel demand models at an aggregated level across the discrete choice model. These attributes can be added to the travelers' decision-making mechanism separately through the disaggregated level of data in agent-based simulation. The main drawback here is that the modal choice that is embedded in the agent-based approach as an element of the genetic algorithm, is not well investigated. Hörl et al. (2018) tried to integrate discrete choice modeling into co-evolutionary algorithm in MATSim. However, consistency of the proposed integration method and its compatibility with the other part of the multi-agent framework remain uncertain.

3.3 Methodology

The investigation performed in this chapter is based upon the multi-agent transport simulation MATSim (Horni et al., 2016) and its Dynamic Vehicle Routing Problem (DVRP) extension (Maciejewski, 2016). In the following, a short introduction of the simulation framework is given. Further details are provided in Chapter 2.

MATSim uses the artificial population with an initial daily plan for each agent as an input. The plans incorporate activities that are performed throughout a day with their respective arrival times, locations, and durations as well as the initial transport modes, which agents use to move between two activity locations. The daily plan could exceed 24 hours, but the simulation is done for a single day only. In the first simulation, each agent realizes its plan for the given day. A dynamic queue-based model measuring the traffic flows and estimating the travel times simulates the movements of agents from one activity to the next. It is possible that due to congestion or crowded public transport some agents arrive too late to the next activity location. Likewise, some others might arrive too early. Any deviation from the initial activity plan (especially start time) for each agent is memorized and measured by a score in the end of the day. In addition, an extra score is calculated for the mode that has been used. For the next iteration, agents try to slightly modify their plan (e.g., the mode that they use for each trip or activity end-time) to diminish the less negative score. The iteration is repeated until the average overall scores of the executed plans in the population start to fluctuate slightly around an equilibrium state. This evolutionary re-planning and learning process is the core component of the simulation.

The measurements (i.e., scoring) in the simulation are based on two general occurrences: activities and trips (or legs). Scores are described by marginal utility of activities and marginal disutility of legs. Utility is measured through time and equivalent cost-varying parameters. However, score functions can be set for each agent according to its corresponding sociodemographic attributes or personal preferences. In order to integrate user trust and willingness to use SAVs in this simulation and to address the previously discussed research gap, we propose to extend the modeling approach detailed later in this chapter.

This chapter is organized around three major parts: (i) categorized scoring function, (ii) population synthesis, and (iii) scenario set-up and model calibration.

3.3.1 Categorized scoring function

Some major changes are required to integrate systematic taste variations among individuals. In MATSim the scoring function is based on the Charypar-Nagel scoring method (Charypar and Nagel, 2005). The function includes both activity and leg scores. Since the purpose of this chapter is to add the new mode and anticipate short-term changes, only leg (trip) scores are modified. The initial leg scoring function is described as below:

$$S_{trav} = C_{mode} + \beta_{trav,mode} \times t_{trav} + \beta_{mode,dist} \times d_{trav} \dots \quad (3.1)$$

where for each mode in a leg the score is calculated from constant utility of mode C_{mode} , marginal disutility of travel duration $\beta_{trav,mode}$, travel time t_{trav} , marginal disutility of travel distance $\beta_{mode,dist}$, and the distance traveled between two activity locations d_{trav} . Furthermore, mode-specific

additional terms (e.g., waiting time for public transport) may be added separately. A more specific scoring method is developed based upon the initial function, by employing Logit Model, to develop utility equations, and to estimate the total disutility of travel in the form of generalized costs. Moreover, the function is categorized by travelers' socio-professional categories in order to integrate the different behavior of travelers according to their personal attributes. Furthermore, this categorization can help us to differentiate the similar daily activity pattern of groups of individuals according to their main daily activity tour. The proposed scoring function is the following one:

$$S'_{trav,cat} = \kappa_{ut} \times C_{m,cat} + \beta_{trav,m,cat} \times VoT(\kappa_{ivt} \times t_{ivt} + \kappa_{wt} \times 10 \times t_{wt}) + \beta_{trav,m,cat} \times Cost_m(d_{trav}) + \nu_{co,m,cat} + \gamma_{pl,m,cat} \quad (3.2)$$

where

- $S'_{trav,cat}$ is the utility (score) of travel performed by mode m and by traveler category cat
- κ_{ut} is the user trust factor which equals to “1” for all modes except SAVs
- $C_{m,cat}$ is the constant utility of mode m by traveler category cat
- $\beta_{trav,m,cat}$ is the marginal disutility of travel cost of mode m by traveler category cat
- κ_{ivt} is the willingness to use factor of in-vehicle travel time utility which equals to “1” for all modes except SAVs
- t_{ivt} is the in-vehicle travel time
- κ_{wt} is the willingness to use factor of waiting time utility which equals to “1” for all modes except SAVs
- t_{wt} is the waiting time
- VoT is the nominal value of time
- $Cost_m$ is the travel cost for mode m by traveler category cat
- d_{trav} is the travel distance
- $\nu_{co,m,cat}$ is the dummy factor of household car-ownership (one, two and more) for mode m by traveler category cat
- $\gamma_{pl,m,cat}$ is the dummy factor of parking availability level at destination (medium and high) for mode m by traveler category cat

All parameters except additional factors are derived from the utility functions estimated for each socio-professional category. For SAVs, given that this mode is not yet widely available and consequently the marginal disutility cannot be estimated from the RP surveys and discrete choice model, another approach has been devised. According to a recent survey conducted in France that addressed 457 persons with different individual attributes and current modes (presented in Chapter 2), car users are much more likely to use SAV when the service is proposed with a fixed monthly cost and unlimited rides. Based on this survey, we assume that the marginal disutility of in-vehicle travel time for SAV service is similar to individually owned cars. Moreover, the marginal disutility of waiting time is

assumed ten times bigger⁹. These naïve assumptions do not fully reflect the real behavior of travelers regarding the use of a future SAV service, but given the purpose of this chapter, i.e., to explore the impact of user trust and willingness to use variations on SAV service performance and fleet size, those assumptions are acceptable.

The above-mentioned survey shows that user trust varies according to the age and gender. In general, men are more likely to use an SAV than women. Similarly, younger persons are more likely to use SAVs in comparison to older ones (further details are provided in Chapter 2). In our simulation, in order to integrate user trust, we assume that the constant utility of mode SAV varies according to those attributes. This is given by using variable user trust factor:

$$\kappa_{ut} = 2 - \frac{(\kappa_{Age} + \kappa_{Gender})}{2} \quad (3.3)$$

where different variations with the mean value equal to one are supposed for age factor κ_{Age} and gender factor κ_{Gender} . These variations are derived from the results of the aforementioned survey and the distribution graph is based on it (Fig. 3.1). Concerning gender, two fixed values are assumed for the distribution. Additionally, a different variation is supposed for the age preference factor κ_{Age} : for both persons younger than 45 years and older than 60 constant values are considered respectively, and for middle-age travelers this factor changes linearly.

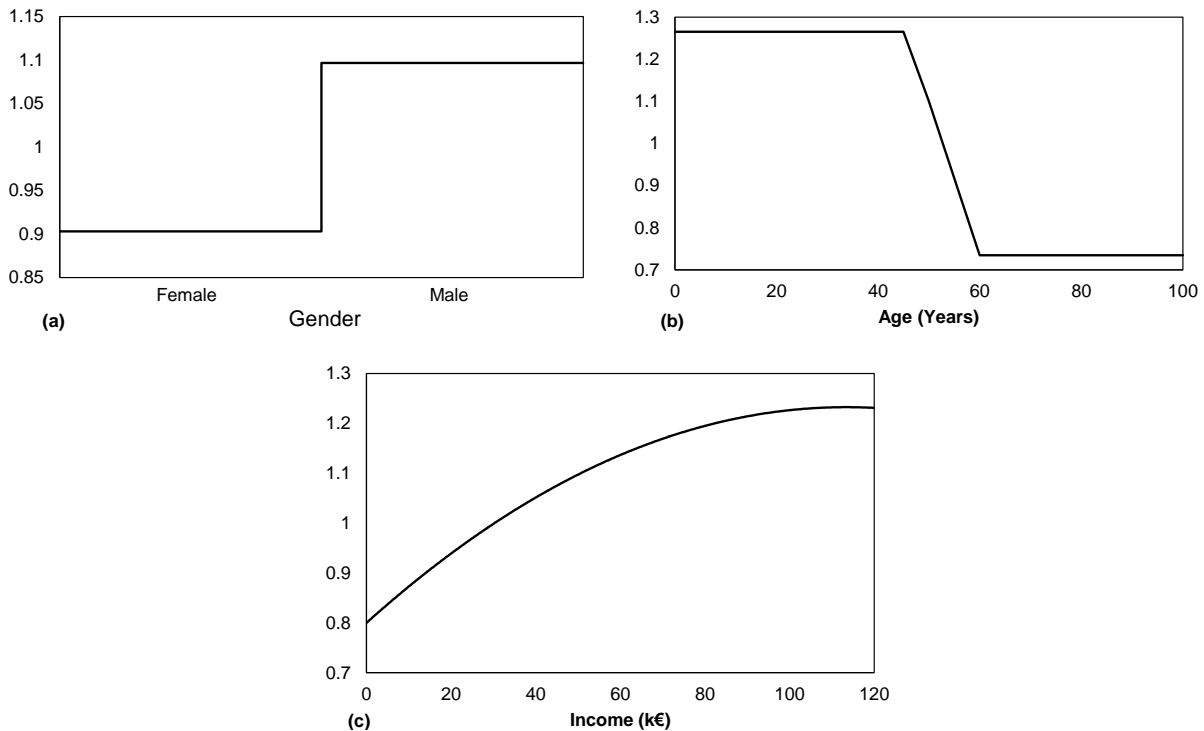


Fig. 3.1. Distribution graphs of SAV user systematic taste variation factors, (a) gender, (b) age, (c) income.

⁹ In the simulations conducted in Chapter 4 and Chapter 5, the value of waiting time is considered 1.5 times larger than the value of in-vehicle travel time (Wardman et al., 2016).

According to the survey results, the SAV willingness to use is strongly correlated with the service cost. Therefore, we assumed that the perception of in-vehicle and waiting times varies with income:

$$\kappa_{ivt} = \frac{1}{\kappa_{Income}} \quad (3.4)$$

$$\kappa_{wt} = \kappa_{Income} \quad (3.5)$$

where the in-vehicle factor κ_{ivt} is inversely correlated with income. As wealthy persons are more likely to use this service compared to less fortunate, the income factor κ_{Income} is assumed to grow logarithmically. However, because of the higher value-of-time (VoT) for wealthy persons the waiting factor κ_{wt} is assumed to vary directly when income grows.

All of the above-mentioned attributes as well as socio-professional categories have been identified and defined for each traveler in the population synthesis.

3.3.2 Population synthesis

The synthetic population is an essential input for multi-agent transport simulation. The population synthesis is based on the sociodemographic data of individuals and households. As this microdata is not available for the whole population, a synthetic population is generated. This is done by drawing households and individuals from microdata samples on a zonal level. In the case of multi-agent transport simulation, more detailed information related to the individuals' activity and travel patterns must be synthesized. In this thesis, the second process is called "activity chain allocation".

As stated above, we aim to set the scoring function according to the socio-professional attributes of each individual. It is therefore mandatory to have those data for the population. Popular procedures for population synthesis include both the generation of a joint multiway distribution of all attributes of interest using iterative proportional fitting (IPF) and combinatorial optimization (CO). Recognizing their limitations, including the inability to deal with multilevel controls (e.g., controls on the socio-professional attributes), as well as the need for determining a joint multiway distribution, a novel method is proposed. The process is as follow: while a set of households is drawn randomly from the sample, a multilevel controller measures the fitness of marginal synthetic and real data by zone and by attributes of interest. This procedure is called "fitness-based synthesis with multilevel controls (FBS-MC)". An open source generator was developed (Fig. 3.2) which is applicable for synthetic population generation for all large cities in France (Kamel et al., 2018).

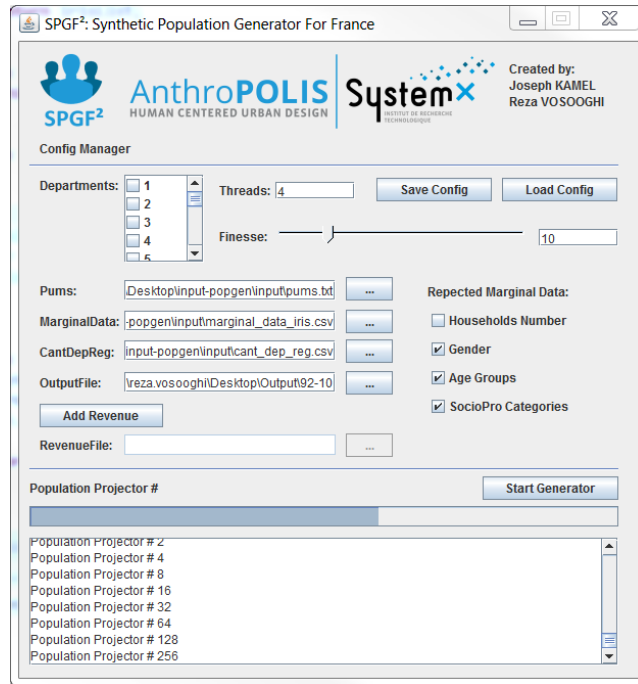


Fig. 3.2. Synthetic population generator (fitness-based synthesis with multilevel controls), applicable for large regions in France.

Once the synthetic population is generated, the next step is to allocate activity chains to each individual. This was done using the frequency of each activity chain in the transport survey according to socio-professional attributes. By analyzing the transport survey of the case study area, it is found that the activity chains are significantly correlated with those attributes, especially in the case of “Employed” persons, “Students” and “People under 14 years of age” (Fig. 3.3).

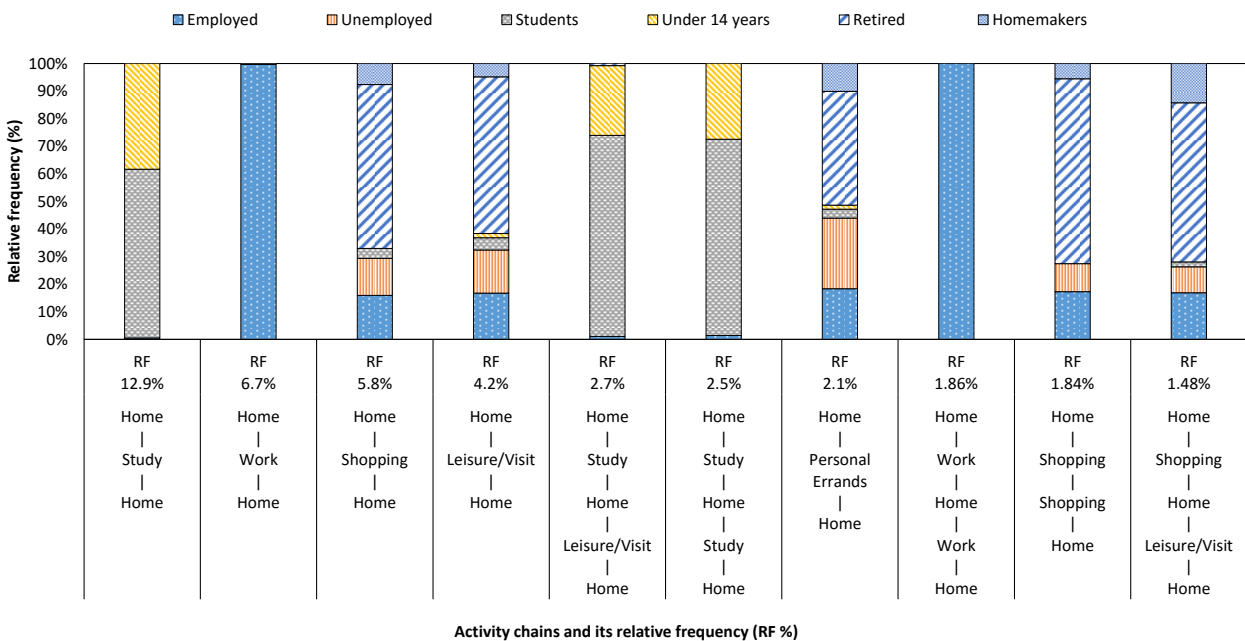


Fig. 3.3. Top ten activity chains of Rouen-Normandie metropolitan population and the frequency of socio-professional categories of individuals.

3.4 Scenario setup

The base scenario of this thesis was created for the Rouen-Normandie metropolitan area with a population of around 484,000 inhabitants and a 58,892-link network (Fig. 3.4). The synthetic population is generated from public use microdata (INSEE 2014) and the regional transport survey (EMD Métropole Rouen Normandie 2017) relying on a simulation-based synthesis. The multilevel controller was set up to generate the population with the minimum errors for household numbers, age ranges and socio-professional category attributes.

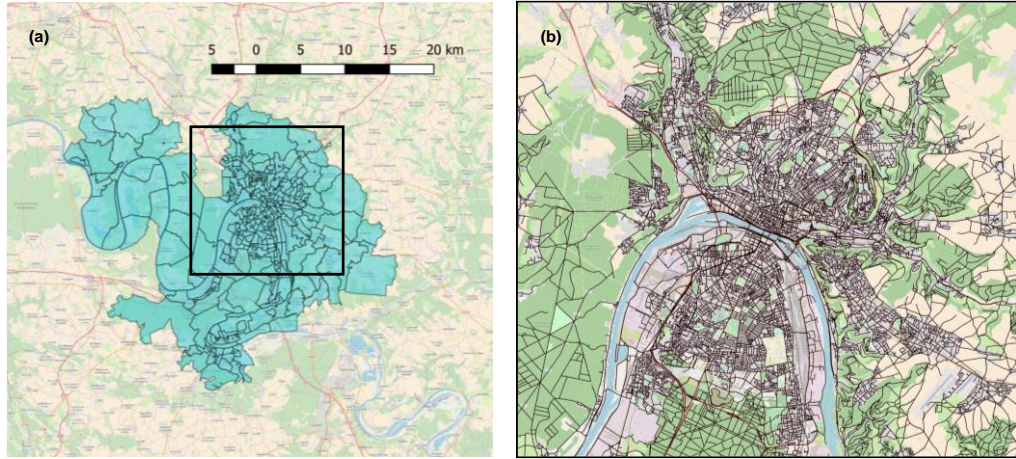


Fig. 3.4. (a) Simulation baseline scenario area with 240 population zones, a 58,892-link network, and around 484,000 inhabitants, (b) Fine-grained road network of the city of Rouen.

Fig. 3.5 shows the relative errors of synthetic and real population estimated from the marginal data for all the population zones (IRIS) by age ranges and socio-professional categories of population. As can be seen from this figure, due to small samples for people under 5 and above 79 years old as well as people categorized in the first socio-professional group of the population (i.e., “Farmers, Craftsman, Traders and Entrepreneurs”), the estimated errors are relatively high.

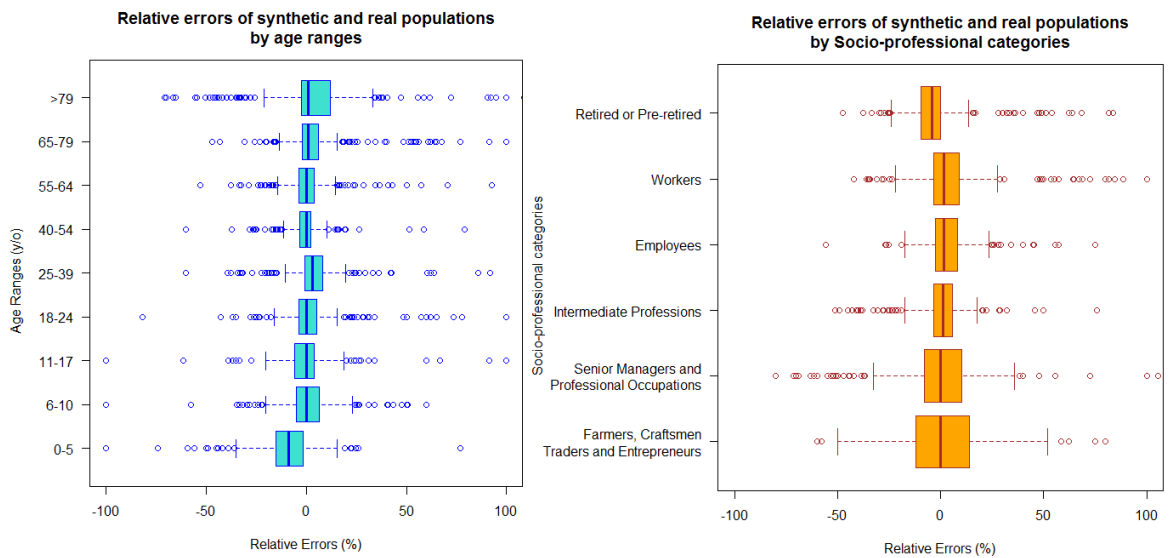


Fig. 3.5. Relative errors of synthetic and real population estimated from the marginal data for population zones.

For each individual of the population an activity chain is then assigned. This is done based on the analysis of a recent transport survey (EMD Métropole Rouen Normandie 2017). 929 different activity chains are found for eight trip purposes in the observations (Fig. 3.6), including around 5,000 households and 11,000 individuals, for which 19 are common for 50% (red line), and 124 for 75% (blue line) of the surveyed people. All the activity chains are assigned to the synthetic population according to the socio-professional categories by frequency.

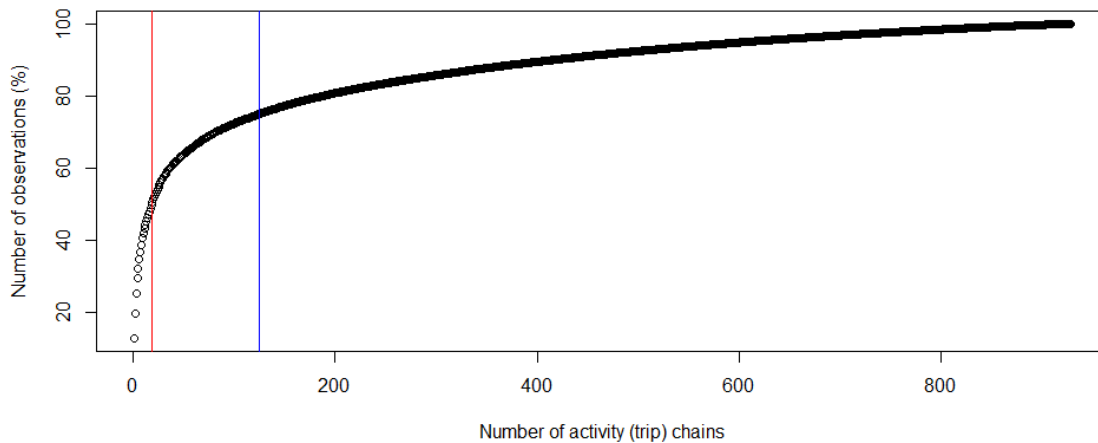


Fig. 3.6. The frequency of different activity chains estimated from regional transport survey (EMD Métropole Rouen Normandie 2017).

In the next step, for each activity of individuals, a location is assigned. This process is carried out based on the origin-destination estimation derived from the PUMS and the regional transport survey. For each individual in PUMS and accordingly in the synthetic population, the aggregated locations of “Home”, “Study” and “Work” activities are known. In order to assign the relevant locations for other activities (i.e., “Other Work”, “Leisure”, “Shopping”, “Family/Personal Errands” and “Escorting”) a simplified model is developed. This model estimates the probability of destination zones according to the origins and destinations activity types. Once activity zones are known, the next categorical model assigns the exact location within each zone according to the facility’s specific type. The distribution is done using the gravity distance model.

The final step is to allocate the start time and the duration to each individuals’ activity. Statistics on these data are measured from the regional transport survey. Subsequently, categorized models are developed. Fig. 3.7 shows the kernel distributions (smoothing functions¹⁰) of start time for different activity types. As can be seen from this figure, for almost all activity types there are two peak hours (in the morning and evening). For “Study” trip purpose, the morning peak hour is much more important and deviation from this peak is more limited due to the strict start time of educational institutions. The second peak for “Work” and “Other Work” activities originates from secondary activities (such as lunch or visit). The models for “Shopping” and “Family/Personal Errands” are relatively similar and only the evening peak hour for “Shopping” lasts longer. The peak times for “Leisure/Visit” is shifted to the right and it seems that those activities are performed more during lunch or dinner times. The “Home” activity

¹⁰ A kernel distribution sums the component smoothing functions for each data value to produce a smooth, continuous probability curve.

start time here refers to returning to home between other activities during the day as well as the end of the daily activities. The peak start time for this activity match obviously with other ones. Only a small peak of the beginning of the day is present in this model, which is derived from the “Escorting” activity of “Homemakers” in the survey.

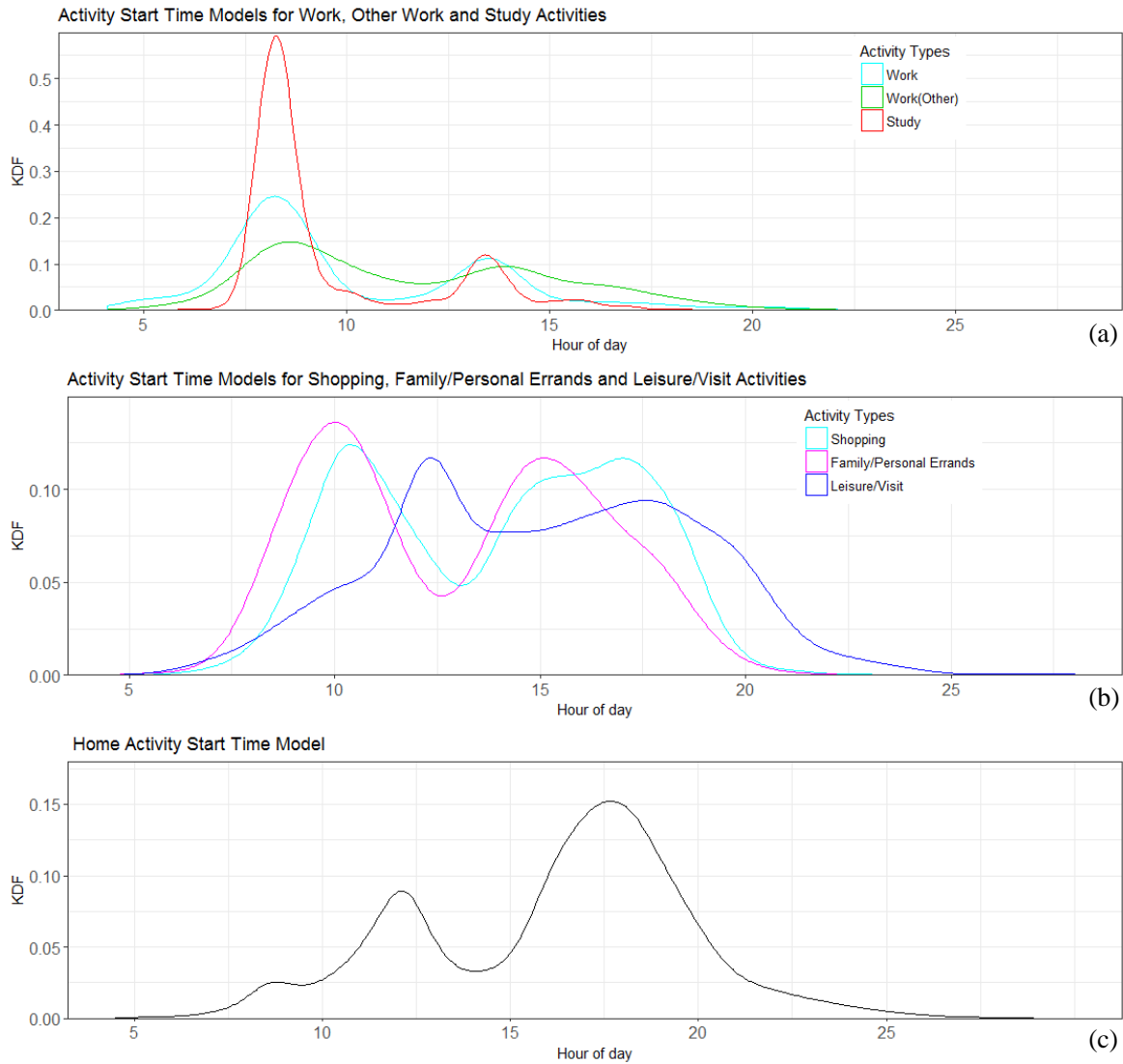


Fig. 3.7. Activity start time models estimated from regional transport survey (EMD Métropole Rouen Normandie 2017).

Fig. 3.8 shows the plotted kernel distribution estimates of activity duration for different activity types. Activity duration models of “Study” and “work” purposes are almost similar. The two peaks here are due to the middle activities, which are more “Home” and “Leisure/Visit” ones. However, for “Other Work” (i.e., work at an unusual location, meetings, missions, etc.) the behavior of the model is completely different. In the case of “Shopping” and “Family/Personal Errands”, there is an important peak for a short duration and then, the frequency has an inverse correlation with the duration of the activity. For the “Home” activity during the day, a similar behavior is given, with the difference that the correlation has a slighter slope.

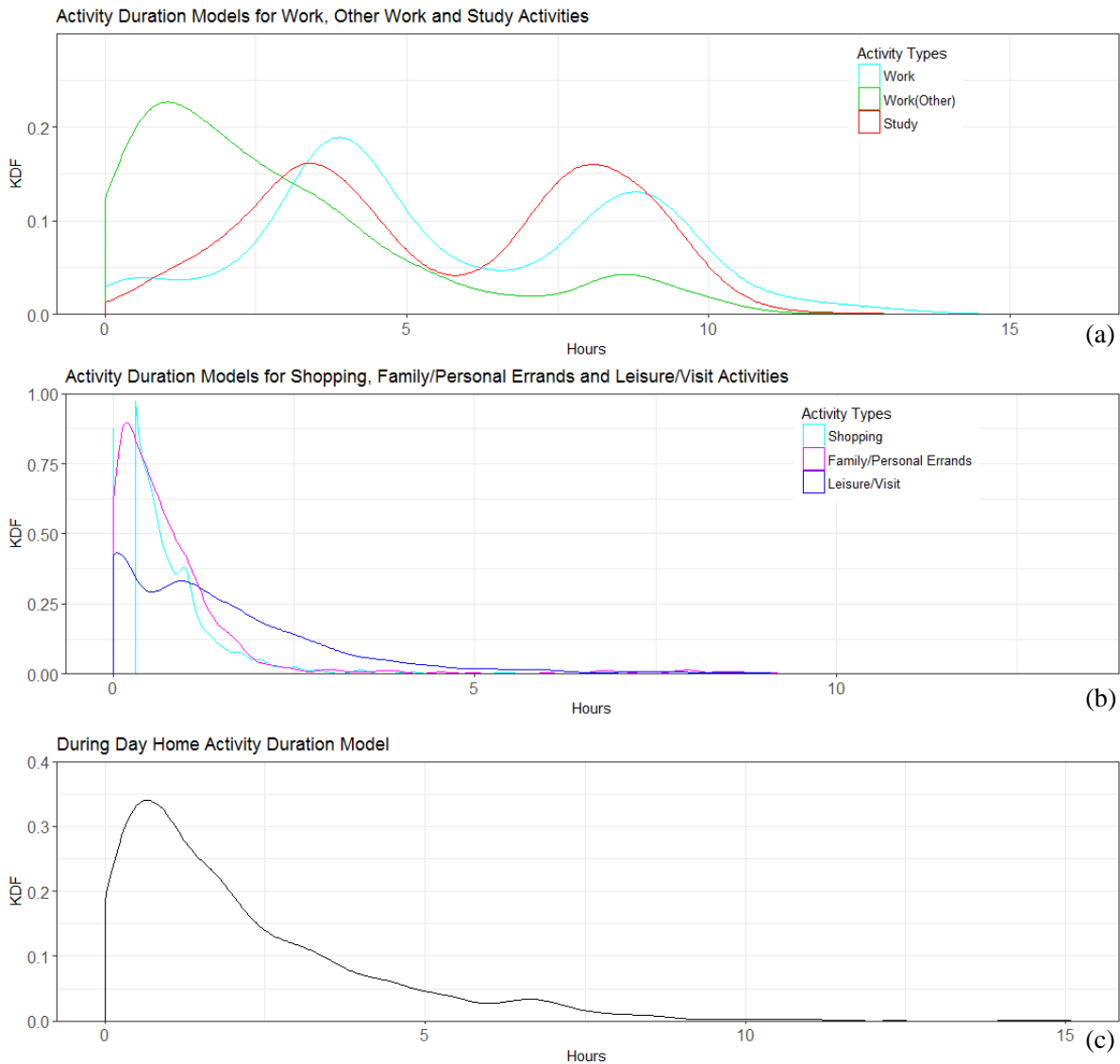


Fig. 3.8. Activity duration models estimated from regional transport survey (EMD Métropole Rouen Normandie 2017).

The described models is used to assign time-related characteristics of the allocated activities to the synthetic population by socio-professional categories. The multi-agent simulation is performed over this fine-grained synthetic population. The next step is to set up the model. For this purpose, the utility functions for the transportation system of the case study area are estimated for each socio-professional category. These estimations are based on data obtained from the recent transport survey (EMD Métropole Rouen Normandie 2017). The scoring function are set up accordingly (Table 3.1).

Table 3.1
Estimated parameters of categorized scoring function.

	Employed	Unemployed	Retired or Pre-retired	Students, unpaid trainees 14 years of age or older	Under 14 years	Homemakers
Car						
C (utility)	-3.6020	-2.7890	-2.5520	-3.8919	10.7037	-4.2870
β_{trav} (utility/€)	-0.1062	-0.1290	-0.3794	-0.2962*	-0.4286	-0.5477
$Cost_m$ (€/km)	-0.3000	-0.3000	-0.3000	-0.3000	-0.3000	-0.3000
v_1 (utility)	2.6257	3.3000	1.7200	1.8292	2.9565	3.0860
$v_{\geq 2}$ (utility)	3.3727	3.5930	2.4910	2.3111	3.9719	5.0510
γ_m (utility)	-0.1465	2.3770	-0.4820	-1.7695	-15.2280	-0.1020
γ_h (utility)	-0.7282	-2.2050	0.1040	-1.4279	-15.1742	0.3920
PT						
C (utility)	-3.9290	-2.2850	-3.6290	-2.2643	11.4187	-4.6340
β_{trav} (utility/€)	-0.0327	-0.0910	-0.2088	-0.2385*	-0.2191	-0.2202
v_1 (utility)	-0.7330	0.0350	-1.0540	0.1292	-0.4358	0.2950
$v_{\geq 2}$ (utility)	-1.0170	0.1710	-1.7670	0.1848	-0.7283	1.0570
γ_m (utility)	0.5606	-2.5320	1.4040	-1.4570	-14.6497	0.9190
γ_h (utility)	0.9463	-1.0530	1.1650	-1.0114	-14.3791	1.0200
Walk						
C (utility)	0	0	0	0	0	0
β_{trav} (utility/€)	-0.8137	-0.7236	-0.7308	-3.0852*	-0.8051	-0.8708

*These values represent an estimation based on the logarithm function of corresponding variables.

In the development of utility equations, in order to estimate the level-of-service (LoS) it is assumed that the nominal VoT for all trip purposes and all travelers is equal to 10 €/hour (DG Trésor (2018)). However, on the simulation since this value is multiplied to income factor, the assumed VoT varies for all travelers according to their income level. As estimated from the survey, the modal split of cab is almost zero; as a result, the models do not include this mode. Based on data of the average French drivers, the relevant non-fixed costs of car (the marginal disutility of travel distance) is assumed 0.3 €/km (DG Trésor (2018)). Likewise, the public transport price is set at 1.43 €/trip (ticket price when sold in book of 10 full fare tickets) and the walking speed at 5 km per hour.

The simulation is afterwards calibrated according to the modal splits of the case study area by varying the constant utility of modes. Concerning SAVs, as there is no RP data at hand, some assumptions for the valuation of parameters are required. As stated above, two marginal disutility of travel duration measures are assumed for SAVs: in-vehicle and waiting times. For in-vehicle time, the marginal disutility of travel duration is considered the same as for car, and for the waiting time, it is assumed ten times bigger. Additionally, it is assumed that SAV service has the fixed monthly cost rate (one and a half times bigger than the fixed cost of car) with unlimited rides for the users.

3.5 Simulation results

In order to serve the 1,508,160 person-trips ten scenarios of non-ridesharing SAVs with various fleet sizes have been generated. Four initial distribution points are assumed in the simulation. The service has been considered available during the whole day. All requests for SAV service are made by customers right before departure; there are no in advance bookings. Moreover, ingress and egress times are supposed to be one and two minutes respectively. These scenarios are evaluated with and without

considering user trust and willingness to use SAVs, and analyzed in terms of fleet usage, in-vehicle passenger kilometer traveled (PKT), and average passenger waiting time.

Fig. 3.9 shows modal shares for all scenarios. The results illustrate that SAV modal share increases proportionally to the fleet size. Consistent with findings in the literature (Hörl et al., 2016; Martinez and Viegas, 2017; Vinet and Zhedanov, 2011), modal shifts toward SAVs come mainly from public transport, car and walk, but the use of public transport decreases significantly relative to other ones. The overall changes on SAV modal shares for the same fleet sizes vary from 1.5% to 4.4% with two significant values for the fleet sizes of 2,000, 3,000 and 7,000 vehicles.

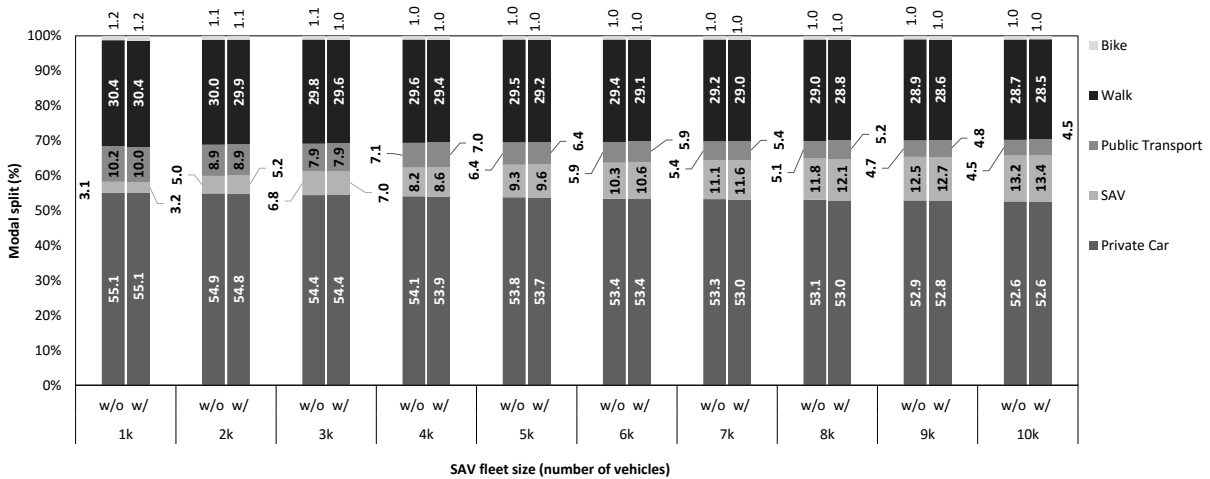


Fig. 3.9. Modal split comparison for various fleet sizes without and with considering user trust and willingness to use SAVs.

By comparing average passenger waiting time, service demand, and average PKT, with and without considering user trust and willingness to use SAVs, one can observe that these indicators vary for all fleet sizes with unlike ratio but with similar trends (Fig. 3.10). The difference on average passenger waiting time is positive and less than 1.1 minute for all scenarios. However, there are two major changes on service demand and average PKT in the fleet sizes of 3,000 and 7,000 vehicles. In fact, for the scenario without considering individual taste variation, the maximum demand with all vehicles occupied at least for one hour is met with about 6,000 SAVs in operation; while considering user trust and willingness to use, more than 7,000 SAVs are needed to reach this goal (Fig. 3.11). Therefore, the significant changes for fleet size of 7,000 SAVs comes mainly from the overall demand. However, for the scenario with 3,000 vehicles important differences occur due to some other factors.

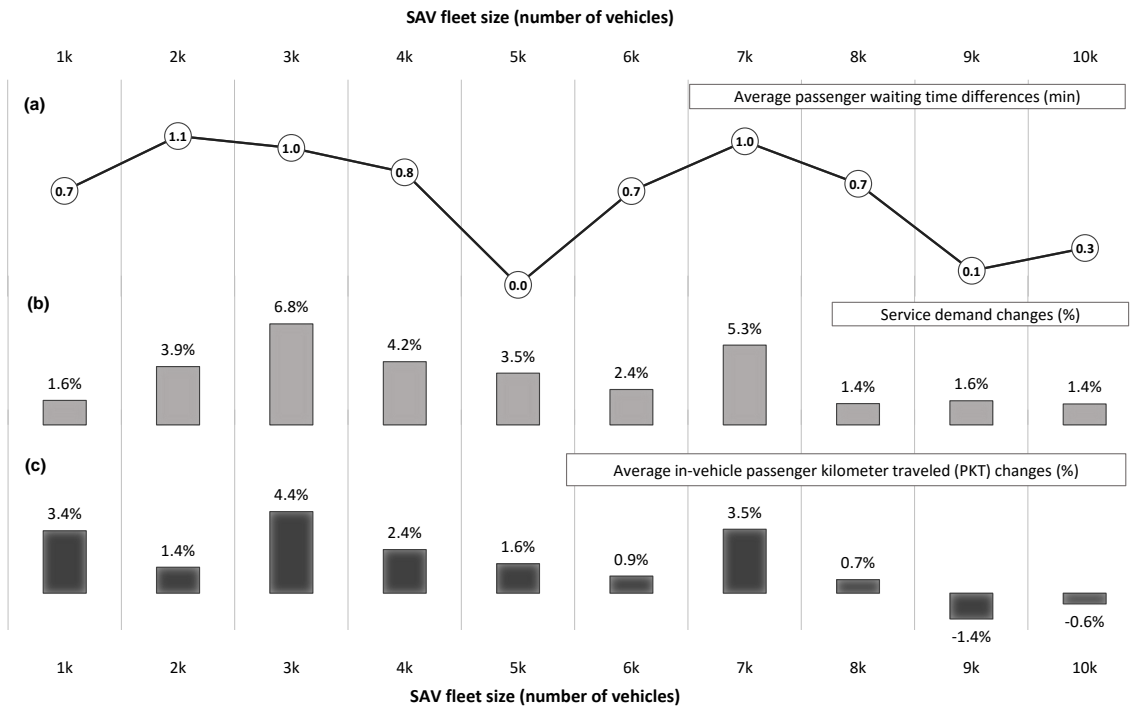


Fig. 3.10. SAV service and user-related relative changes before and after the introduction of user trust and willingness to use SAVs for various fleet sizes (a) average passenger waiting time differences, (b) service demand changes, and (c) changes on average in-vehicle passenger kilometer traveled (PKT).

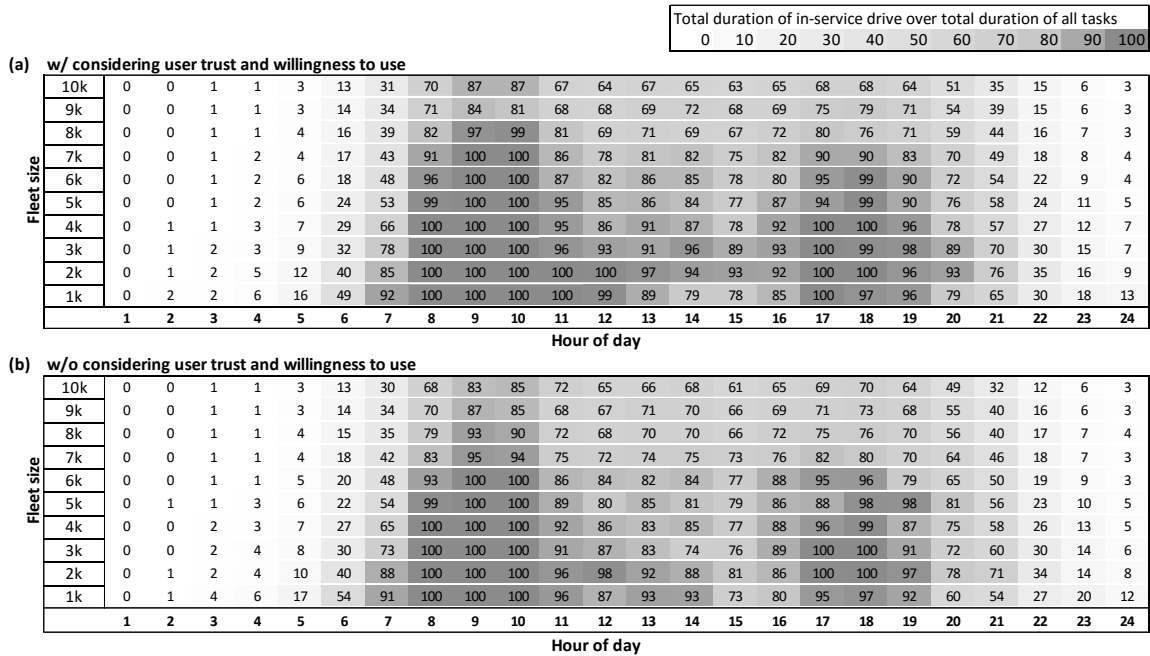


Fig. 3.11. Hourly SAVs in-service rate (a) with, and (b) without considering user trust and willingness to use SAVs.

The changes on SAV service demand after introducing user trust and willingness to use are due to the user’s variation in terms of sociodemographic attributes and socio-professional profiles (Table 3.2).

As mentioned before, women and elder people are less likely to use an SAV. As a result, “Retired people” and “Homemakers” used less SAVs in almost all scenarios compared to those when user trust and willingness to use are neglected. In the contrary, “Students” and “Persons under 14 years” used this mode more significantly. However, the average trip distance especially for “Persons under 14 years” is shorter than for “Retired people” and “Homemakers” (Table 3.3). Thus, the fleet is available to serve larger number of users and the overall demand increases for all fleet sizes. Regarding to “Employed” people, the change on SAV service usage remains minor for all scenarios. However, for “Unemployed” people some fluctuations can be observed especially for the fleet size of 7,000 vehicles. Once there are enough vehicles to serve all demands (e.g., more than 7,000 SAVs), the indicators become more stable except for “Homemakers”, which is due to the limited number of users in this profile.

Table 3.2

Changes on SAV service users grouped by socio-professional categories after considering user trust and willingness to use SAVs.

Profiles	Fleet size									
	1,000	2,000	3,000	4,000	5,000	6,000	7,000	8,000	9,000	10,000
Employed	-2%	1%	4%	0%	2%	2%	4%	3%	1%	3%
Unemployed	5%	0%	3%	1%	8%	1%	14%	1%	6%	3%
Retired or pre-retired	4%	-31%	-12%	-11%	-31%	-24%	-18%	-16%	-18%	-17%
Students >14 years	12%	36%	39%	35%	24%	26%	25%	13%	15%	12%
< 14 years of age	5%	11%	24%	5%	6%	9%	7%	6%	8%	10%
Homemakers	-29%	-21%	-31%	-2%	-28%	-42%	-16%	-28%	-7%	-11%

Table 3.3

Comparison of entire population attributes and average trip distance by socio-professional categories.

Profiles	Population, female/male (% of total)	Average Age (year)	Average Household Income (€)	Average Trip Distance (m)
Employed	51.0 / 49.0	41	26 623	15 190
Unemployed	48.8 / 51.2	35	22 968	13 516
Retired or pre-retired	56.9 / 43.1	73	25 272	14 209
Students >14 years	42.4 / 47.6	19	29 715	14 001
< 14 years of age	49.2 / 50.8	7	29 415	9 482
Homemakers	98.1 / 1.9	49	29 517	16 196

As discussed before, travelers with different socio-professional categories and consequently dissimilar daily trip patterns have a different willingness to use SAV service for their trips. Therefore, by introducing this variation, SAVs are used in a different temporal pattern. Fig. 3.11 shows the hourly SAV in-service rates of all scenarios and prove the abovementioned variation. Two peaks related to peak hours can be observed from this figure. As illustrated by color intensity, peak areas corresponding to the case of considering user trust and willingness to use SAVs have higher values especially for the fleet size of between 2,000 and 7,000 vehicles. Meanwhile, almost SAVs are in service from 8 a.m. to 8 p.m. in the second and third scenarios in which individual taste variation are considered. As mentioned above, the service use for “Students”, “Persons under 14 years”, “Retired” people, and “Homemakers” have significantly changed in those scenarios and especially in the case of a fleet size of 3,000 SAVs. People of different profiles have different temporal trip pattern, particularly those related to their

secondary activities. However, these results can be intensely different for other case study areas with dissimilar sociodemographic structure.

The other observation obtained from Fig. 3.11 is that the maximum fleet usage occurs when the fleet size is between 2,000 and 3,000 SAVs in both cases, with and without considering user trust and willingness to use SAVs. One can conclude that in the case of minimum fleet size (1,000 SAVs), the passenger waiting time is relatively high and the users choose other means of transportation instead of SAVs. Meanwhile, by increasing the fleet size, the passenger waiting time decreases and the utility of using SAV service becomes relatively competitive compared to other modes until the maximum demand reached.

The fleet usage is one of the key parameters that helps planners to size the fleet and to evaluate service performance. In order to illustrate the differences in two cases, relative changes on average daily and peak hour in-service rates are compared (Fig. 3.12). The average in-service rate has been defined as the total duration of in-service drive over the total duration of all tasks (including stay task, when there is no demand for an SAV). The peak hours are assumed 8-10 a.m. and 5-7 p.m. As can be seen from Fig. 3.12 while average daily in-service rate changes after introducing individual taste variation are significant for the fleet sizes of 3,000 and 7,000 vehicles, for the fleet sizes of less than 5,000 SAVs, the average morning peak hour in-service rate remains unchanged. This is due to the excessive demand for the SAV service in the morning peak. Considering average evening peak hour in-service rate, the changes are more scattered with a significant increase for the fleet size of 7,000 vehicles.

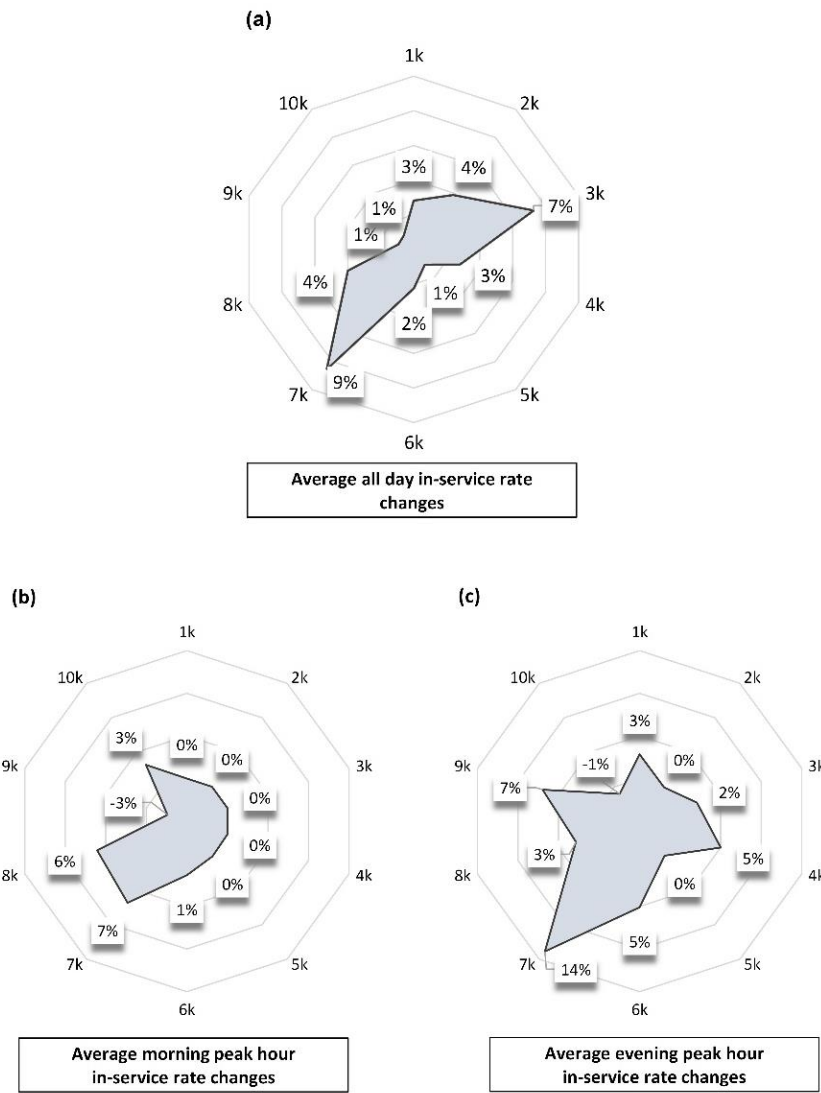


Fig. 3.12. Comparison of average in-service rate changes before and after the introduction of user trust and willingness to use for various SAV fleet sizes for (a) all day, (b) morning peak hour, and (c) evening peak hour.

The overall fleet usage rate during a day could meaningfully change service profits of operators. Fig. 3.11 shows that by introducing individual taste variation the hourly service use in off-peak hours changes especially in the case of the small fleet sizes. Fig. 3.13 illustrates this difference; an important alteration for the fleet size of 3,000 vehicles is observed. This is also the reason for which the other key indicators for this fleet size change expressively.

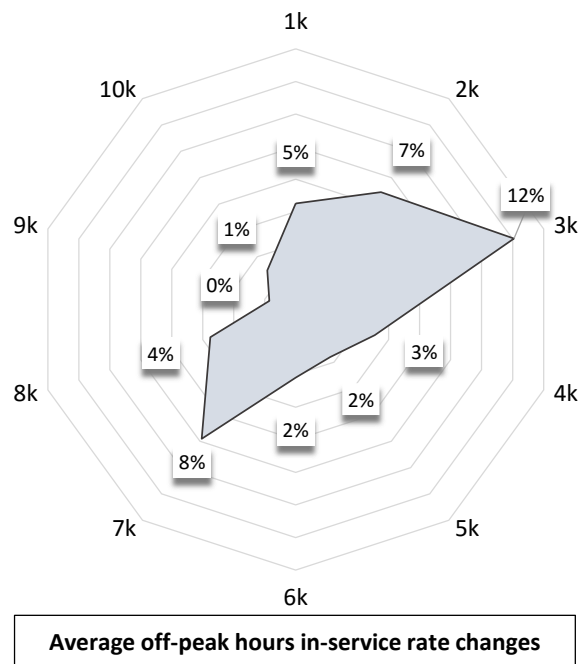


Fig. 3.13. Comparison of average in-service rate changes for off-peak hours before and after the introduction of user trust and willingness to use for various SAV fleet size.

These results indicate that by introducing user trust and willingness to use SAVs, the significant changes are occurred for two fleet sizes. The first one in the case of the fleet required to meet the maximum demand (with all vehicles in-service at least for one hour), and the second one for the fleet size in which the maximum usage is approximately met (less than about a half size of the first case). Meanwhile, in the latter case, as all the vehicles are in-service in the morning and evening peak hours, off-peak SAV service demand becomes notably the main cause to affect overall service indicators. As mentioned before, this is largely due to the diversity of users having different temporal daily trip patterns. Unlike other indicators, the passenger waiting times remain almost stable for all fleet sizes.

3.6 Conclusion

In this chapter, the scoring function of MATSim, which is the simulation platform of the proposed modeling and simulation framework, was categorized and modified to integrate user trust and willingness to use SAVs into the model. The transportation system of the Rouen-Normandie metropole area with ten different fleet sizes of non-ridesharing SAVs was simulated. The outputs were analyzed in terms of fleet usage, temporal distribution of in-service rides, customer waiting times and average PKT throughout a day. The results reveal significant changes not only for the fleet size required to meet maximum demand, but also for a smaller fleet size. User diversity in terms of socio-professional profiles (with different temporal trip pattern) and different value of waiting time are the main reasons for those changes.

The above discussions of user trust of SAVs, willingness to use and travel demand pattern variations are key to operator costs and system profitability. Fleet variation can have important consequences for costs and customer experience. Moreover, operators will want to size their fleets to maximize profits, while offering users a relatively high level of service. The results indicate that SAV service configuration

and particularly fleet sizing must be taken into account according to the demographic structure of the region of interest along with the preferences variation of its inhabitants.

Next chapter aims at extending this framework in order to perform a more comprehensive analysis of SAV service design and performance evaluation for both non-ridesharing and ridesharing SAV services with distance-based cost rates and by using relevant performance metrics. Assessing the spatial aspect of services (e.g., relocation strategy and charging station locations in the case of electric SAVs) by considering the spatial dispersion of travelers with different profiles can result in clearer predictions on the use of SAVs in real-world scenarios. These are the subject of next investigations in Chapter 4 and Chapter 5. Furthermore, vehicle-related aspects of SAV service operation such as vehicle capacity and range, and their impacts on service performance are assessed.

Chapter 4

Shared Autonomous Vehicle Service Design

The success and competitiveness of future SAV services depend on their operational models, which are linked intrinsically to the service configuration and fleet specification. Configuration of SAV service according to the balanced tradeoff between proposed service and demand is a key factor in the SAV service design. Using a comprehensive framework of SAV simulation in a multimodal dynamic-demand system with integrated SAV user taste variation, this chapter evaluates the performance of various SAV fleets and vehicle capacities serving travelers across the Rouen Normandie metropolitan area in France. Furthermore, the impact of ridesharing and rebalancing strategies on service performance is investigated.

4.1 Introduction

Today's mostly experimental SAV services are modified versions of ordinary electric cars with four or five seats inside. However, it is still uncertain how the most efficient design of these vehicles would look like. In addition to the vehicle characteristics and features, operational aspects of this new service could intensely influence its success. Some configurational characteristics such as fleet size, allocation and relocation strategies, service area, and infrastructures have a direct impact on the parameters that are important for mode choice decision of travelers. Although travel time and cost are the most important parameters in this regard, in the case of a shared system, some other parameters such as waiting time and detour time (in the ride share mode) are of great significance. Moreover, the variation of individuals' attitude toward using this system may significantly affect service performance. In particular, the absence of a driver in SAV may generate an important concern for travelers and consequently result in lower demand. Thus, all of these parameters have to be considered in the upstream planning for having an accurate estimation of service performance measures.

Due to recently developed approaches, especially multi-agent simulation, parameters important for mode choice decision of travelers can be reflected at a fine-grained level. Potentially, earlier multi-agent activity/tour-based simulations are able to consider the complex supply-demand relationships of the multimodal transportation system. Various aspects of operating future SAVs are the subject of current research efforts based upon this approach. In particular, some in-depth investigations have been recently carried out on SAV fleet optimization, rebalancing, and cost structures of operational models (Bösch et al., 2018; Hörl et al., 2019; Loeb and Kockelman, 2019). In several studies, the human-related side of driverless cars and their impacts on service demand have been assessed (Kamel et al., 2018; Vosooghi et al., 2019a). The impact of ridesharing on the operational efficiency of SAV has also been the subject of few investigations (Farhan and Chen, 2018; Hörl, 2017). However, to the best of our knowledge, none of these studies considers all affecting aspects of SAV operation at the same time. The present chapter addresses this gap by conducting comprehensive dynamic-demand simulations in a multimodal network. The analysis of given simulation outputs allows investigating the effects of different operational components and vehicle specifications (specifically vehicle capacity) on the efficiency of the offered service, considering dynamic-demand responsive to the network and the LoS, and by integrating user taste variations and value-of-travel-time (VoT). Simulation experiments in this chapter are also based upon the real data for the transportation system of the Rouen Normandie metropolitan area in France using the proposed framework of modeling and simulation presented in Chapter 2.

The remainder of this chapter is structured as follows. Section 4.2 reviews the relevant researches on this topic. Section 4.3 presents the model specification and set-up process. Section 4.4 describes overall results, as well as detailed analysis categorized by each service aspect. Finally, Section 4.5 provides insights gained through this chapter.

4.2 Prior research

To date, numerous investigations have been conducted on SAV demand modeling and simulation particularly in the last 5 years. Several approaches have been developed to anticipate the demand for future SAV services. These approaches are presented and analyzed in Chapter 2. Given the purpose of the current chapter –i.e., conducting comprehensive simulations considering all factors affecting the

designing of the SAV services – a review of more specifically multimodal simulations incorporating dynamic demand that are responsive to the network and traffic, with more details is provided in as follows.

Several studies have integrated SAVs into the area where private cars are not allowed or they are all replaced by the new service. Azevedo et al. (2016) proposed an integrated agent-based traffic simulator built on disaggregated behavior models in both demand and supply (SimMobility) to study the potential impacts of introducing an AMoD service in a car-restricted zone of Singapore. In this work, individual preferences to use autonomous vehicles were kept unchanged and only the cost of the service was assumed as 40% less than the regular cab and TNC services in Singapore. The studied AMoD system employs autonomous mid-size sedans without sharing rides. Their simulation is performed through some optimization processes in terms of facility location, vehicle assignment and routing, and vehicle rebalancing. Their results suggest that rebalancing results in higher demand. In addition, the passenger waiting time is strongly correlated with the fleet size and number of parking stations. However, further growth of those variables has no more impacts once an optimal demand is reached. Heilig et al. (2017) used an agent-based travel demand model with macroscopic traffic simulation to evaluate the transportation system of the Stuttgart region where all the private cars are replaced by an AMoD service. They performed simulation for more than one day (one week) and analyzed the changes in overall transportation system performance. Furthermore, the fleet required to fulfill the demand is investigated. In their simulation, the cost per mile of a proposed service is assumed 70% less compared to the private cars and the user preferences are kept unchanged. The simulation encompasses the relocation strategy during nighttime, and it is shown that total vehicle mileage decreases up to 20% after the introduction of a new AMoD service. Martinez and Viegas (2017) tried to explore the potential outcomes of so-called radical change in urban mobility configuration of Lisbon region after introducing shared mobility services based upon a spatially aggregated agent-based simulation. In the simulated scenarios, all private mobility and conventional buses are replaced by ATs and Taxi-Buses. Their simulation incorporates several optimization models in order to assign dynamically the vehicles or generate them if needed for a given day. Based on their results, it is inferred that congestion and emissions would strongly decline by introducing those shared services. Chen and Kockelman (2016) employed a multinomial logit mode choice model in an agent-based framework to assess various dynamic pricing strategies on mode shares estimate of electric SAV in Austin. Due to the spatial aggregation, the mentioned study ignores trips under one mile and non-motorized modes. Since SAV travelers can use their in-vehicle time to do other activities, the VoT for this mode in the mentioned study is considered variable and dissimilar to transit. The simulation includes private cars, transit, and electric SAV. According to the performed analysis, electric SAV modal share changes significantly by variations of VoT and service fares. Besides, it is shown that some service operational metrics can be improved via targeted pricing strategies. Wen et al. (2018) in a comprehensive study investigated the deployment of AV and SAV services as the last-mile solution focusing on operation design. They employed a detailed nested logit structure for the mode choice model. In their study, an agent-based simulation is used to estimate the LoSs. They showed that there exists an important trade-off between fleet size, vehicle occupancy, and traveler experience in terms of service availability and response time. Although the mentioned research incorporates SAV user preferences by varying the alternative specific constant in the mode choice model, it includes only the unobserved (undetected) parameters of mode choice decision and neglects user specific attributes.

All the above-mentioned studies incorporate discrete choice modeling as a traveler decision choice mechanism. In some other studies, however, utility scoring is used instead. Hörl (2017) utilized MATSim to evaluate the dynamic demand of autonomous cab service. This researcher integrated two service operators into the simulation and system performance and compared operational indicators. A fleet of 1000 AVs is introduced to the transportation system of the city of Sioux Falls in all scenarios. The simulation results reveal that the service with ridesharing attracts a larger number of travelers at off-peak hours. Liu et al. (2017) simulated a fleet of non-ridesharing SAVs integrated into the road network of Austin, using the same simulation framework. Within this study, different SAV service fares and fleet sizes are assumed and modal share as well as the impact on energy use and emissions are investigated. The authors concluded that higher SAV fares result in fewer long trips with SAVs. User taste variations are not considered in the two mentioned studies. In Chapter 3, the same framework (MATSim) is used to explore the impact of user trust and willingness to use on fleet sizing of SAV service integrating to the transportation system of Rouen Normandie. The simulation is performed using the categorized utility scoring according to the individual sociodemographic attributes of users. The results obtained from our previous study presented in Chapter 3 (also available in Vosooghi et al. (2019a)) shows the significant importance of traveler trust and willingness to use varying the SAV service use and the required fleet size. This work benefits of several optimization models to assign the vehicles dynamically. However, the study incorporates SAV services without ridesharing and rebalancing strategy.

Table 4.1 presents a summary of the mentioned studies stating their objectives and the main features.

Table 4.1

Summary of the selected literature on SAV demand modeling and service simulation*.

Author(s), year	Demand estimation approach/ Mode choice mechanism	Vehicle characteristics	SAV user preferences	Assessment purposes
Azevedo et al., (2016)	Activity-based multi-agent simulation/ Hierarchical discrete choice modeling	Mid-size sedans w/o ridesharing	Unvaried	Impact assessment, determine the fleet size and parking stations requirements
Chen and Kockelman, (2016)	Activity-based multi-agent simulation/ Multinomial logit mode choice modeling	NM	Variable (willingness to pay, the-value-of travel-time)	Sensitivity assessment of pricing strategies E-SAVs mode shares
Heilig et al., (2017)	Activity-based multi-agent simulation/ Discrete choice modeling	Standard 4-seats w/ ridesharing	Unvaried	Impact assessment, determine the fleet size
Martinez and Viegas, (2017)	Trip-based multi-agent simulation/ Discrete choice modeling	6-seats minivan w/ ridesharing	Variable (car ownership, public transport pass)	Impact assessment, impacts on car fleet size, the volume of travel and parking requirements, CO ₂ emissions
Hörl, (2017)	Activity-based multi-agent simulation/ Utility scoring	Standard 4-seats w/ and w/o ridesharing	Unvaried	Dynamic-demand simulation of AVs and SAVs
Liu et al. (2017)	Activity-based multi-agent simulation/ Utility scoring	Non-ridesharing	Unvaried	Assessing different SAV service fares, impacts on energy use and emissions
Wen et al., (2018)	Trip-based multi-agent simulation/ Nested logit mode choice modeling	Standard 4-seats w/ and w/o ridesharing	Variable (intrinsic preference)	Design of last-mile AV and SAV services integrated to public transit
Vosooghi et al., (2019a)	Activity-based multi-agent simulation/ Categorized utility scoring	Standard 4-seats w/o ridesharing	Variable (age, gender, and household income)	Impact assessment of user preferences on individual-ride SAV fleet sizing

* In this table only studies which perform multimodal simulations with dynamic demand that is responsive to the network and traffic, are presented.

Some other studies investigate the use of SAV services in a multimodal system incorporating various dispatching strategies or pricing schemes. However, the demand of the proposed services in these simulations is not necessarily dynamic (Farhan and Chen, 2018; Hörl et al., 2019) or responsive to the traffic states (Chen et al., 2016; Fagnant and Kockelman, 2018, 2014). Many other studies incorporate static or predefined demands (Boesch et al., 2016; Fagnant and Kockelman, 2014; Levin et al., 2017) or simulate only one mode (Bischoff and Maciejewski, 2016b; Loeb and Kockelman, 2019; Zhang et al., 2015a). There are also large in-depth investigations on AV dynamic assignment (Hyland and Mahmassani, 2018), ride-share matching optimization problem (Agatz et al., 2011; Alonso-Mora et al., 2017), and SAV rebalancing and ridesharing (Spieser et al., 2014; Zhang et al., 2015b). These studies focused rather on optimization problems and ignored mode choice mechanism in a multimodal context or time-dependency in travel time caused by congestion.

Table 4.1 shows that most of earlier comprehensive simulations to investigate the operation of SAV service are based on the homogeneous structure of behavior in terms of sociodemographic attributes, except our previous work (Vosooghi et al., 2019a), presented in Chapter 3, that incorporated only non-ridesharing service. Hence, the vehicle characteristics and specifically vehicle capacity and its impacts on SAV service performance have remained a missing component in all prior studies. Service cost and the need for enabling rebalancing strategy have similarly received low attention. Considering all mentioned SAV simulation features, to the best of our knowledge, the present study is the first comprehensive investigation of a real-world scenario that could provide new insight into the design of such service.

4.3 Model specification and set-up

4.3.1 Simulation framework

In this work, the multi-agent transport simulation (MATSim) (Horni et al., 2016) and its Dynamic Vehicle Routing Problem (DVRP) extension (including the Demand-Responsive Transport (DRT) application) (Bischoff et al., 2017; Maciejewski et al., 2017) are used. The main idea behind MATSim is the simulation of an artificial population, represented by agents, who perform their respective plans including activities and movements between activity locations throughout a day. The movements are simulated within a dynamic queue-based model in which all agents interact dynamically with each other in a network (traffic simulation). At the end of the simulation day, which usually exceeds 24 hours due to the longest activity chain, all agents evaluate the performance of the executed plan by measuring and scoring the deviations from the initial plan and the utility of using a mode. This process is called “utility scoring”. In the next iterations, agents try to maximize their scores by modifying their plans. This “re-planning” process is performed rather by using another mode and route or by ending an activity sooner than at its planned end time. The more agents explore potential alternatives, the more they learn about their optimal plans. Once the convergence on the total score is reached, agents stop to innovate their plans and try to select one plan from their memorized set of plans and to find out the plan with the best score. This is repeated until a systematic relaxation is reached.

Re-planning is usually done after the plan execution and traffic simulation. However, for the simulation of new transportation systems and specifically those that need a cyclic re-computation of vehicle tasks and routes (e.g., SAV, on-demand services with multiple requests), instant decisions must

be made while the traffic simulation is running. Such a decision making is possible using dynamic agent module included in DVRP-DRT extension (Maciejewski, 2016), which directly interacts with the traffic simulation of MATSim.

4.3.2 *Ridesharing and rebalancing*

For the purpose of this chapter, the dispatch algorithm of ridesharing developed by Bischoff et al. (2017) is used and integrated into the proposed modeling and simulation framework (presented in Chapter 2). The dispatch algorithm performs a centralized on-the-fly assignment of vehicles to on-demand requests. This optimizer returns a list of requests and vehicle paths between pick-up and drop-off points. In order to route SAVs dynamically, an insertion heuristic that aims to minimize the total SAVs workload is employed. The SAVs workload is measured as the total time spent on handling requests. This leads to a lower detour for each user. The optimization process seeks also to decrease vehicle usage for more requests, which results in more service availability and consequently greater demand. During the simulation, when a new request is submitted, the algorithm searches the routes of all vehicles for optimal insertions. An insertion is feasible when it satisfies the following conditions: (i) the overall travel time constraints (including waiting and in-vehicle times) are satisfied for already inserted requests (passenger(s) on board) and (ii) the expected boarding times for the awaiting and upcoming requests need to remain within a defined time frame. All feasible insertions are then evaluated and the first insertion that offers the smallest increase of vehicle work time will be selected. If no feasible insertion is found, the request is rejected. A request can be rejected (e.g., due to constraints violation) only immediately after submission, and already accepted requests cannot be rejected or re-scheduled.

We employed the rebalancing strategy that is included in the DRT extension of MATSim, which is based on the Minimum Cost Flows problem. In this problem, one seeks to “optimize” the time-varying flows on each arc between aggregated demand hubs and idle vehicles, taking into account congestion effects along arcs and at nodes. Idle vehicles are relocated in regular intervals according to the estimated demand of the previous iteration. The expected demand for the next 60 minutes is considered in the optimization process.

It is important to underline that the selected dispatch and rebalancing algorithm may have a strong impact on service performance indicators (Hörl et al., 2019; Hyland and Mahmassani, 2018). Particularly, when the demand for SAV service is relatively high, applying simplified assignments (e.g., FIFO) can lead to the worst service efficiency (Hyland and Mahmassani, 2018). However, we found that the employed strategies for vehicle assignment and relocation are accurate enough for our purpose. Furthermore, it is important to note that the multi-agent simulation already adopts heuristic rules in feedback loops to achieve approximate convergence and consistency between multidimensional decisions and network loading. Thus, it may require even more computational resources to achieve equilibrium when very sophisticated heuristic rules are applied to find good assignment and relocation of vehicles.

4.3.3 *Inputs and model setup*

As mentioned earlier, the main goal of this chapter is to design an SAV service considering all affecting operational and user-related aspects. For this purpose, the simulation inputs are based on real activity chains replicating the traveler patterns and schedules derived from the transport survey and

census. Fig. 4.1 illustrates the overall framework. A synthetic population for the case study area is generated using an open source generator developed previously (Kamel et al., 2018) that applies fitness-based synthesizing with multilevel controls. Some major attributes such as age, gender, household income range, and socio-professional category are used for controls. These are the attributes with an important impact on SAV mode choice (see Chapter 2) or are the joint attributes of synthetic population and activity models. The activity chains are then allocated to each synthetic individual according to their socio-professional attributes. Based on transport survey analysis conducted for two French case study areas (Paris and Rouen Metropolitan area), it is found that the activity chains are significantly correlated with those attributes (Kamel et al., 2019; Vosooghi et al., 2019a). The socio-professional category consists of six groups of persons: “Employed”, “Unemployed”, “Students”, “People under 14 years”, “Retired”, and “Homemakers”. The generated synthetic population is validated by comparing relative errors of the synthetic and real population in each zone for estimated and given marginal data of each attribute (for more details see Chapter 3).

For two main trip purposes (“Work” and “Study”), the fine-grained geographical zones of activity are given in the census data. For other trip purposes, an origin-destination matrix based on the transport survey is estimated. Both of these data are employed in the process of activity chain allocation. In the latter case, for each trip origin in each zone, a destination zone according to the probability of trip purpose by socio-professional category is allocated. Then, the activity’s precise locations are randomly appointed along the zone in keeping with existing activity types and land-use category.

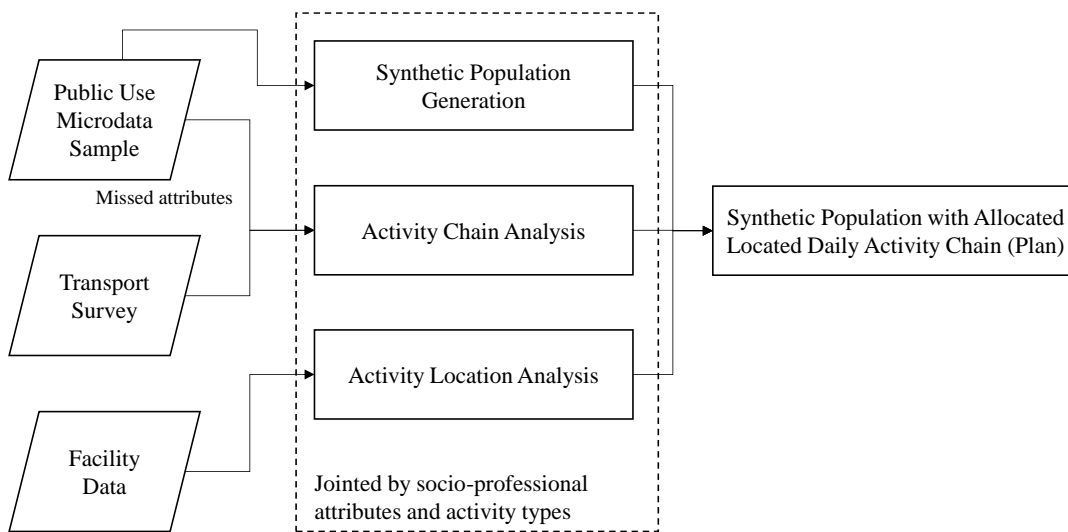


Fig. 4.1. Synthetic population generation and activity chaining framework.

In MATSim, utility scoring is performed based on the Charypar-Nagel scoring method (Charypar and Nagel, 2005). The function includes both activity and leg scores. In conducted simulations, due to the lack of data only legs’ scoring utilities are set according to the utility functions estimated from the recent local transport survey (EMD Métropole Rouen Normandie 2017) by employing a logit model. The activities’ performing score is, however, assumed proportional to that used in other similar studies. The proposed scoring function is the following one:

$$S'_{trav,cat} = \kappa_{ut} \times C_{m,cat} + \beta_{trav,m,cat} \times VoT(t_{ivt} + \kappa_{wt} \times 1.5 \times t_{wt}) + \beta_{trav,m,cat} \times \frac{1}{\kappa_{ivt}} \times Cost_m(d_{trav}) + v_{co,m,cat} + \gamma_{pl,m,cat} \quad (4.1)$$

where

- $S'_{trav,cat}$ is the utility (score) of travel performed by mode m and by traveler category cat
- κ_{ut} is the user trust factor which equals to “1” for all modes except SAVs
- $C_{m,cat}$ is the constant utility of mode m by traveler category cat
- $\beta_{trav,m,cat}$ is the marginal disutility of travel cost of mode m by traveler category cat
- κ_{ivt} is the willingness to use factor of in-vehicle travel time utility which equals to “1” for all modes except SAVs
- t_{ivt} is the in-vehicle travel time
- κ_{wt} is the willingness to use factor of waiting time utility which equals to “1” for all modes except SAVs
- t_{wt} is the waiting time
- VoT is the nominal value of time
- $Cost_m$ is the travel cost for mode m by traveler category cat
- d_{trav} is the travel distance
- $v_{co,m,cat}$ is the dummy factor of household car-ownership (one, two and more) for mode m by traveler category cat
- $\gamma_{pl,m,cat}$ is the dummy factor of parking availability level at destination (medium and high) for mode m by traveler category cat

In addition to travel time (including waiting time) and travel cost, user’s car-ownership, as well as parking availability at destination, were found to be significant parameters in the mode choice model. Thus, they are incorporated into utility scoring. In the simulation employed in this chapter, the value of waiting time is considered 1.5 times larger than the value of in-vehicle travel time (Wardman et al., 2016). The detailed list of parameters as well as the estimations are described in Chapter 3.

In the ridesharing algorithm, the detours are set up so that the ride times can be extended up to 30% of the direct distance. Bigger detour times for passengers are allowed only if their waiting times do not surpass 15 min. However, in that case, the SAV ride is more penalized in terms of utility (scoring). During the simulation,

4.3.4 User taste variation

User taste variations were integrated into the model based on the methodology proposed in Chapter 3. In order to set up the model according to the travelers’ perception and a tendency toward using SAVs, an online survey was made (Chapter 2, Al-Maghraoui, 2019). Users’ trust and subjective criteria behind their willingness to use were identified. We found that the socio-professional and three other sociodemographic attributes (i.e., income, age and gender) are significant to SAV taste variations among individuals. For instance, the above-mentioned survey shows that in general men are more likely to use an SAV than women. Similarly, younger persons are more likely to use SAVs compared to older ones.

In order to integrate these variations into the simulation, all the utility scoring and functions are estimated and set up separately for each group of users within the same socio-professional category. The marginal time and cost-varying parameters in the scoring function are then multiplied by the factors of user trust and willingness to use so that the score (utility) of SAV for the similar trips varies according to the sociodemographic attributes of travelers including age, gender and household income range.

4.3.5 *Simulated scenarios*

In order to apply the proposed modeling and simulation approach to design an SAV service for a real-world scenario, the Rouen Normandie was chosen as the case study. Rouen was a fitting venue for at least three reasons. First, the access to the most recent transport survey (EMD Métropole Rouen Normandie 2017) was provided. Second, the population (about 484,000 inhabitants) and the metropolitan area network sizes allow to perform the simulation with an acceptable downscaling rate (10%), which results in quite accurate outputs compared to the full-scale model (Bischoff and Maciejewski, 2016b). Actually, in some studies relying on agent-based simulation and utility scoring, the population of case study areas is highly downscaled (less than 1%) due to the high computational time. This extensive downscaling may potentially affect the service performance evaluations considering the spatiotemporal interaction of supply and demand in large study areas. The third reason for choosing this area is that some experiments on self-driving cars are currently undertaken; thus, it is possible to gain data on traveler behavior in a near future and to integrate them to the extended simulations. Furthermore, Rouen Normandie is a promising candidate for replacing existing private modes with an SAV service, especially in the Rouen old town.

To support the simulation of such a scenario, the synthetic population from the PUMS (INSEE 2014) was generated. Based on the local survey including 5,059 households and 11,107 individuals, 929 activity chains including eight trip purposes were found. As mentioned before, the activity chains and time profiles were allocated to the synthetic individuals according to their socio-professional category.

The simulations were run for several fleet-size and fleet-capacity scenarios with and without considering ridesharing or rebalancing strategies to appreciate system performance metrics. Regarding SAV, prices of 0.5 €/km for the individual ride (non-ridesharing) and 0.4 €/km (direct distance) for ridesharing services are assumed. These service prices are slightly more expensive than private car ride costs in France (c). Moreover, they are almost similar to the values that have been estimated or concluded in other investigations. For instance, Chen et al. (2016) estimated the price for electric SAV from \$0.66 to \$0.74 per person-trip-mile (about 0.36-0.40 €/km) accounting all costs and operating margins, and Bösch et al. (2018) estimated it 0.43 CHF per passenger kilometer (0.39 €/km). The SAV fleet is initially distributed from four fixed points inside the region and out of old town. Therefore, no “warm-start” - as in Fagnant and Kockelman (2014) - or random distribution are considered.

4.3.6 *Performance metrics*

Although a limited number of studies have simulated SAV service incorporating its dynamic demand, there are several investigations on the performance evaluation of such a system. In this regard, a long list of performance metrics has been used as well. These metrics do not necessarily have the same consequences. For instance, Fagnant and Kockelman (2014) used traveler waiting times in order to estimate required fleet sizes to serve various predefined demands. Since the demand in their study is

considered static, the waiting time could be a relevant indicator to evaluate the service performance. However, as shown in a more recent work of the same authors, the lower in-vehicle and waiting times in a simulation enabling DRS result in higher excess vehicle kilometer traveled (VKT) (Fagnant and Kockelman, 2018) and therefore cannot be the only relevant indicators for the fleet sizing. In this regard, traveler waiting time has been used as a key indicator to define the optimum scenario in some other dynamic-demand simulations (e.g., in Azevedo et al. (2016) or Chen and Kockelman (2016)). However, in this thesis work the term “fleet in-service rate” is proposed to use for the fleet sizing. This indicator is defined as the number of occupied or in-service vehicles (including going to pick up a client) over all vehicles. The other metric representing the proportion of extra VKT (due to the unoccupied or rebalancing mileage) over total VKT will be used in parallel to evaluate empty vehicle traveling distances and to find the balanced trade-off between these two indicators. The detour distance would be among the main traveler-related indicators representing extra travel distances due to the shared rides. The traveler waiting times here will be used as the LoS evaluation; the lower the waiting time, the higher the service level is. In fact, due to the dynamic decision mechanism between available alternatives for each traveler, higher waiting times result in lower SAV demand and consequently service usage. Therefore, this parameter implicitly affects the main performance indicators. With the aim of comparing the service revenues for different scenarios, the in-vehicle passenger kilometer traveled (PKT) is defined. This indicator presents the sum of trip distances traveled by each individual on SAVs. In order to investigate the usage pattern of SAV service in the case of ridesharing, the “on-board occupancy rates by a number of passengers” is proposed. Other metrics used in the dynamic-demand simulations to evaluate the performance of proposed service are the number of persons or vehicle trips (Chen and Kockelman, 2016; Heilig et al., 2017) and average in-vehicle times (Hörl, 2017; Martinez and Viegas, 2017). However, these performance indicators are descriptive rather than consequential and thus will not be used for the fleet sizing and vehicle capacity determination.

To evaluate the overall performance of the transportation system, mode share indicator as in the majority of other studies will be compared. Although this thesis does not incorporate environmental impact measurements, the total distances driven by car and SAV are estimated and compared for all scenarios to illustrate how the congestion would change after the introduction of different SAV services. It is important to note that due to the high uncertainty of future SAV service and infrastructure costs, in this research only transport-related indicators are evaluated and analyzed.

4.4 Case study results

4.4.1 Overview

A base-case scenario (S0) simulation run was conducted without integrating SAV and calibrated using the actual modal shares of the case study area. Next, the SAV service was simulated for various fleet sizes (2,000 to 6,000 SAVs) with individual rides (non-ridesharing) (S1) and for those with ridesharing strategy. In the case of ridesharing, three different vehicle capacities were suggested for the simulation: a small car with two seats (S2), standard 4-seats car (S4), and 6-seats minivan (S6). Table 4.2 illustrates the modal splits for all scenarios. It is noteworthy that given the low modal share of the bike (less than 0.1%) and related changes, this mode was not simulated.

Table 4.2

Modal splits estimated for all scenarios and fleet sizes*.

Scenario	Fleet size Mode	2,000	2,500	3,000	3,500	4,000	4,500	5,000	5,500	6,000
S1 non-ridesharing	Car	59.3	58.8	58.5	58.3	58.0	57.7	57.6	57.4	57.5
	Walk	28.3	28.3	28.2	28.2	28.2	28.2	28.2	28.1	28.1
	SAV	3.1	4.4	5.3	6.0	6.5	6.9	7.2	7.5	7.6
	PT	9.2	8.4	8.0	7.6	7.3	7.1	7.1	6.9	6.8
S2 ridesharing (2-seats small car)	Car	59.1	58.8	58.5	58.3	58.1	57.8	57.7	57.8	57.7
	Walk	28.3	28.3	28.3	28.2	28.2	28.3	28.3	28.2	28.2
	SAV	3.8	4.6	5.2	5.9	6.3	6.5	6.7	6.9	7.0
	PT	8.8	8.3	8.0	7.6	7.5	7.3	7.2	7.1	7.1
S4 ridesharing (standard 4-seats car)	Car	58.9	58.7	58.3	58.1	58.0	57.9	57.8	57.7	57.7
	Walk	28.3	28.3	28.3	28.3	28.3	28.3	28.3	28.3	28.3
	SAV	4.0	4.6	5.3	5.9	6.0	6.4	6.6	6.8	6.8
	PT	8.7	8.3	8.0	7.7	7.6	7.4	7.3	7.2	7.2
S6 ridesharing (6-seats minivan)	Car	59.1	58.8	58.4	58.2	58.0	57.9	57.8	57.8	57.7
	Walk	28.2	28.3	28.3	28.3	28.3	28.3	28.3	28.2	28.2
	SAV	4.1	4.6	5.4	5.9	6.1	6.4	6.8	6.7	6.9
	PT	8.6	8.3	7.9	7.6	7.5	7.4	7.3	7.2	7.1

* Due to the rounding process for each modal share, the sum could exceed or be less than 100%.

Table 4.2 shows that the modal shifts toward an SAV service come from both public transport and car modes. This shift is consistent with findings in the literature (Chen and Kockelman, 2016; Hörl, 2017; Martinez and Viegas, 2017; Wen et al., 2018). However, in the case of big SAV fleet sizes, the public transport mode share decreases significantly relative to the car. This reduction is due to the utility of the proposed service, which is rather similar to the public transport mode. The service cost is also an important factor that encourages public transport users to choose a service that costs a bit more but is more appealing due to the lower travel time. Table 4.2 illustrates an interesting result regarding SAV modal share evolution. As can be expected, by increasing the fleet size, SAV modal shares increase accordingly. However, this growth does not follow the same trend for all scenarios. While SAV modal share in scenario 1 (individual ride) is the lowest one among all scenarios in the case of the smallest fleet size, this metric is conversely the highest for the fleet size of 6,000 vehicles. This result can be explained by the presence of a balanced trade-off between service cost, demand (which affects waiting time) and extra in-vehicle time due to detour distances. In fact, when the waiting time is more important compared to in-vehicle times, which is the case for small fleet sizes, the time-based cost of service could surpass the service cost for users. Therefore, the SAV demand and consequently its modal share decreases. However, in the case of big fleet sizes, as the waiting time is not as important as in the case of small fleet sizes, the in-vehicle time (including detour time) becomes an important factor for the decision-making.

Table 4.3 presents the evolution of total driven distance including private cars and SAVs. By deploying SAV services, this indicator increases in all scenarios. Clearly, having a bigger fleet size in each scenario results in more use of vehicles. However, scenarios with ridesharing strategy have lower total driven distance compared to individual ride (except for the scenario with 2,000 SAVs). This difference is attributed to the higher SAVs' occupancy rates in ridesharing scenarios. Comparison of vehicle capacities shows that in the scenarios with the fleets of 4-seats and 6-seats SAVs, the total driven

distance is slightly lower than when 2-seats small SAVs are simulated (except for the scenario with 2,000 SAVs). Meanwhile, for some fleet sizes, this indicator has the lowest value when 4-seats standard cars are used. The shorter total driven distance of individual ride service and smaller vehicles in ridesharing scenarios when 2,000 SAVs are simulated is because of the relatively much lower service demand, which is due to the low LoS provided in that fleet size.

Table 4.3

Total driven distance including car and SAV modes (million kilometers per simulation day (24h)).

Fleet size	S0 base scenario (W/O SAV)	S1 non-ridesharing	S2 ridesharing (2-seats small car)	S4 ridesharing (standard 4-seats car)	S6 ridesharing (6-seats minivan)
-	8.88	-	-	-	-
2,000	-	10.05	10.06	10.14	10.17
2,500	-	10.50	10.33	10.31	10.30
3,000	-	10.77	10.43	10.43	10.45
3,500	-	10.95	10.61	10.50	10.53
4,000	-	11.12	10.62	10.48	10.53
4,500	-	11.20	10.66	10.55	10.53
5,000	-	11.26	10.60	10.53	10.56
5,500	-	11.31	10.73	10.60	10.59
6,000	-	11.32	10.69	10.58	10.63

Table 4.4 presents a summary of the average number of rides per SAV for all scenarios. As can be seen, in the case of small fleet sizes, the SAVs with bigger capacity satisfy more requests because the expected waiting time is relatively high enough to play a major role in the mechanism of SAV mode choice decision. In the scenarios of SAVs with ridesharing and bigger vehicle capacity, the expected waiting time is shorter compared to the scenarios of the individual ride, thus more rides are satisfied. However, by increasing the number of vehicles, the detour distance becomes a more important parameter and therefore in the scenarios with more places in the vehicles, slightly fewer requests are observed. It should be noted that the expected waiting and detour times are the parameters that are estimated for each synthetic individual (agent) during the simulation. Agents learn about their plans (including trips and activities) and final decisions are made in the last iteration when convergence is reached. Thus, the real and expected waiting and detour times have different values.

Table 4.4

Average number of rides per SAV per simulation day (24h).

Fleet size	S1 non-ridesharing	S2 ridesharing (2-seats small car)	S4 ridesharing (standard 4-seats car)	S6 ridesharing (6-seats minivan)
2,000	11	16	17	17
2,500	16	17	17	17
3,000	17	17	18	18
3,500	17	17	17	17
4,000	17	16	16	16
4,500	17	16	15	15
5,000	16	14	14	14
5,500	15	14	13	13
6,000	14	13	13	13

Fig. 4.2 shows that the average detour time varies between 4 and 7 minutes in all scenarios. Likewise, the average in-vehicle time varies from 37 to 48 minutes. However, the variation of waiting time (excluding the smallest fleet size) for each fleet size remains very slight. It is noteworthy that since the simulations are dynamic-demand, low average waiting times for small fleet sizes are due to the low SAV demand especially during peak hours (particularly in S1 and S2). In fact, for fleet size below a certain size, the expected waiting time increases considerably. Therefore, SAV mode becomes less competitive to other available alternatives in terms of generalized cost, except in the morning peak hour when the LoS of other alternatives are as low as SAV (Fig. 4.3). Thus, the demand for SAV service and consequently estimated waiting time decreases. By increasing the number of vehicles, the expected waiting time declines. However, this time is shorter than a critical waiting time (a value that makes SAV non-competitive in terms of utility), its impact on SAV mode choice becomes minor. As a result, the estimated waiting time follows a very slight decreasing trend particularly in ridesharing scenarios. In the non-ridesharing scenario, the estimated average waiting time falls faster for big fleet sizes. This faster decline by increasing the number of vehicles is explained by the fact that for each request an available SAV can be found in lower direct access distance; however, in the ridesharing scenario, this SAV may not necessarily be without passenger and therefore a relatively higher waiting time is required. Thus, the decrease in average waiting time by enlarging fleet size in ridesharing scenarios becomes slighter.

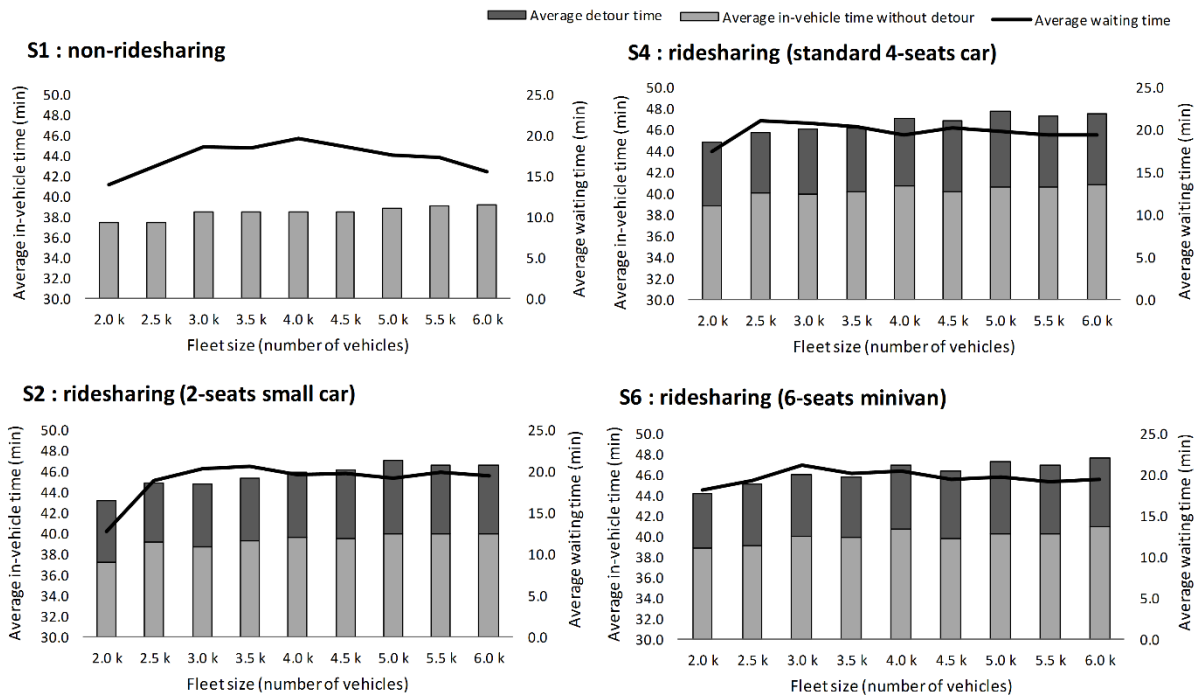


Fig. 4.2. SAV service time variables for all scenarios and fleet sizes.

4.4.2 Fleet size

The bigger fleet size and accordingly the higher SAV modal share do not necessarily lead to a better-optimized operation. In fact, a trade-off between overall expenses and revenues has to be balanced. Service costs include capital expenditure (CAPEX) and operating expenses (OPEX). Since

this research does not incorporate infrastructures of SAV service, CAPEX is assumed directly correlated with the fleet size. OPEX is however associated with fleet usages and mileage. Fig. 4.3 illustrates the hourly fleet in-service rates for all scenarios and various fleet sizes. This figure shows that consistent with daily trip patterns, two peak service usages occur for morning and evening peak hours. However, unlike the SAV modal share, the service use is decreased for big fleet sizes. In fact, by increasing the fleet size, once the fleet usage becomes no longer saturated in the morning peak hour, the latter decreases quickly. This occurs by improving the LoS indicators (waiting time or accessibility in this case) and leads to the demand growth. However, this demand is somehow limited to the number of people who are already likely to choose this service compared to other alternatives that they have, even if the waiting time is very low. Similarly, if the fleet size is small and the LoS is accordingly low, users try to find a more appropriated mode. As a result, as shown in Fig. 4.3, for the small fleet sizes and especially in scenario 1 (individual ride), the fleet usage decreases abruptly. Again, it should be highlighted that the simulation results present the indicators when the interaction of service demand and supply is iteratively relaxed. In other words, the agents have already experienced the SAV service for various level of demands. Agents also tried to slightly modify their activity end time and to depart sooner in order to arrive to the next activity on time. However, the memorized expected waiting time is supposed to be high for many travelers specifically in the case of small fleet sizes. Consequently, SAV is not as used as in the case of medium and large fleet sizes.

Fig. 4.3 shows that in individual ride scenario (S1), SAV service reaches the maximum fleet usage at least for one hour in some fleet sizes. This maximum use, however, does not occur for ridesharing scenarios due to two main reasons. First, in ridesharing scenarios in peak hours there are always SAVs with available seats in the acceptable distance for any requests. Second, since there is no rebalancing strategy in those scenarios (SAVs stay at the same place where the last passenger is dropped off), some SAVs that dropped off a passenger(s) far from demand hubs remain in idle mode at that location and thus the fleet usage does not reach the maximum value. This shows the importance of enabling rebalancing strategy especially when rides are shared among travelers.

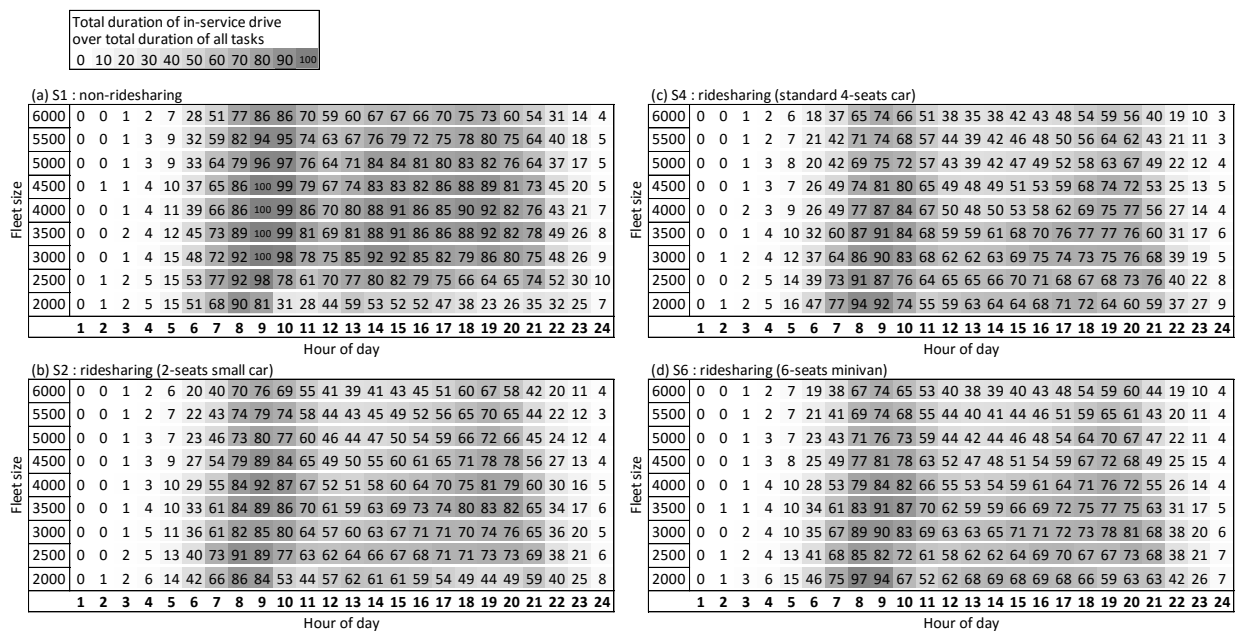


Fig. 4.3. SAV fleet hourly in-service rates.

Empty traveling distance is also a part of fleet usage. High-performance fleet size is characterized by a greater use and a lower empty distance. Fig. 4.4 compares average daily in-vehicle service rates (fleet usage ratio) and empty distance ratio (empty VKT over total VKT) for all scenarios and fleet sizes. As can be seen from this figure, the fleet usage fluctuates more than the empty distance ratio. In fact, by increasing fleet sizes, the empty distance ratio changes only by a maximum of 3%, meanwhile, the fleet usage drops dramatically (up to 16%). This abrupt decline may occur because there is no rebalancing strategy incorporated in those scenarios and the pick-up ride distances remain approximately within the same range of values (with lower usage and consequently more available vehicles, the pick-up ride distance becomes slightly shorter). In order to identify the best performing fleet size, two aforementioned indicators are used. Actually, regardless of any estimations about service operational cost and benefits, the fleet usage indicator can be used as the measure of effectiveness concerning CAPEX. Similarly, the empty distance ratio may be sufficiently indicative for the changes on OPEX term. Since the latter indicator stays rather constant for all fleet sizes, the best fleet sizes are identified according to the fleet usage ratio. For individual ride service, the fleet of 3,500 SAVs, in the case of small cars with two seats, 2,500 vehicles and for the other scenarios, approximately 3,000 vehicles seem to be the best performing size of the fleet.

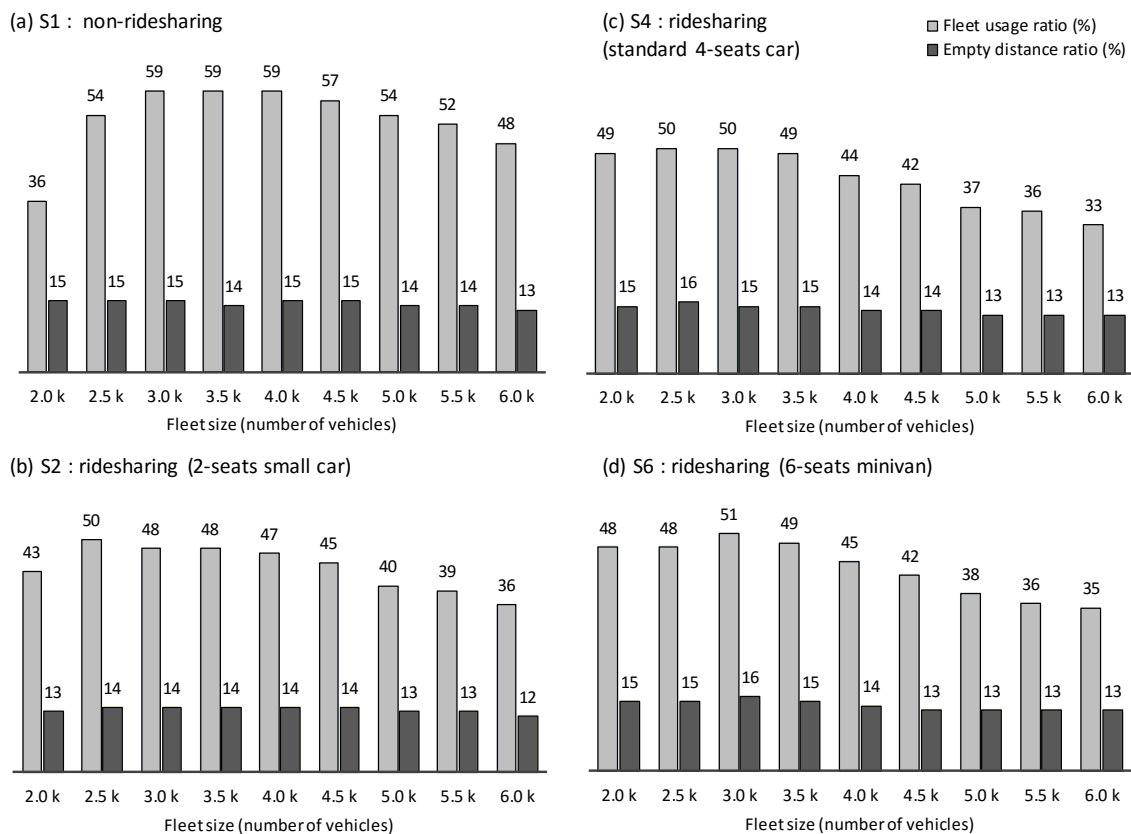


Fig. 4.4. Comparison of fleet usage and empty distance ratios for different scenarios and fleet sizes.

Another noteworthy point in Fig. 4.3 is the shift of the morning peak-hour service usage from 7-9 a.m. for small fleet sizes to 8-10 a.m. for big fleet sizes. This shift is actually due to two main reasons. First, in small and big fleet sizes the SAV users are dissimilar in terms of the socio-professional category

to which they belong. These users have a different trip pattern, consequently by varying fleet sizes the hourly usage of SAV service changes. Second, the possibility of small changes in the activity end-time in the simulation allowed some users to leave the previous activity slightly sooner in order to arrive to the next activity with lower delay. This happens when departing earlier from an origin activity such as “Home” has not an important impact on the score of agent’s whole day plan. However, when the activity at origin is “Work” or “Study”, shorten those activity durations results in a much lower score and penalizes the use of SAV service. The possibility of slight changes on activity end time is enabled for all modes in the simulation, however given the score of performing activities, these changes may not surpass several minutes. Regarding different group of users, in the simulation, agents with different socio-professional category have different utility scoring. In other words, for instance, for some groups of people, the marginal utility of traveling or the value-of-travel-time (VoT) is bigger than for other groups. Furthermore, user taste variation among the different category of travelers affects SAV mode choice. As a result, by increasing fleet sizes and improving the LoS (travel time, including waiting time), the SAV service for some users with different socio-professional categories and accordingly different trip purposes become more attractive (in terms of utility). Since each activity at the destination has a dissimilar model of start-time and duration, hourly usage pattern of SAV service changes when considering a different group of users. Fig. 4.5 illustrates the evolution of SAV service users by their socio-professional categories for different fleet sizes. As can be seen, the ratio of “Employed” people in all scenarios decreases by increasing fleet sizes. For “Students” and “People under 14 years of age”, a slight increase in big fleet sizes is observed. Meanwhile, the changes in the ratio of “Unemployed” people remain minor. However, there is a relatively significant growth in the use of SAV service by “Retired” people and “Homemakers” when the fleet size is large (especially in the case of the individual ride). By comparing scenarios of each fleet size, it can be seen that the SAV service with the individual ride is less attractive for “Employed” and “Unemployed” users. This occurs since the cost-related parameters of mode choice decision are more important than time-related parameters for those groups of users. The above analysis shows the importance of considering users’ profile in estimating fleet hourly usage, which can potentially affect the fleet sizing.

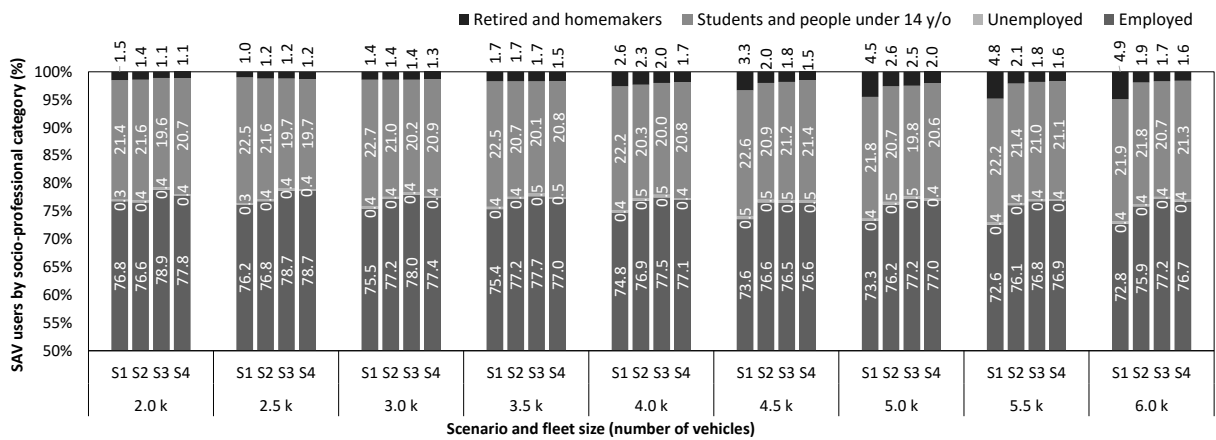


Fig. 4.5. SAV service users by socio-professional category.

4.4.3 The sharing strategy of ride

Fig. 4.3 shows that in the scenarios with ridesharing, the fleets are never 100% in-service for 1-h time slices. This may occur when rides are shared but empty vehicles are not rebalanced. When a request is registered, the nearest occupied vehicle with an available seat and acceptable detour time is assigned. As a result, there are always some vehicles quite far from the demand hubs that are not consequently used for a while. In fact, ridesharing results in relatively lower fleet usage for almost all fleet sizes except for the fleet size of 2,000 SAVs (Fig. 4.4). The more rides are shared, the less the fleet is used. However, each user pays for the provided services and traveled kilometers. In this case, the indicator of in-vehicle passenger kilometer traveled (PKT) may be more relevant. This indicator presents the sum of distances traveled by each individual being on-board SAVs. Fig. 4.6 compares SAV overall PKT for all scenarios and fleet sizes. This figure shows that the overall PKT of the individual ride scenario is minimum for all fleet sizes. This indicator is however almost the same for all ridesharing scenarios in the case of medium fleet sizes (i.e., 3,500 to 4,500 SAVs). By increasing the number of vehicles, the relative difference of PKT between individual ride and ridesharing scenarios decreases. This decline can be attributed to the high LoS provided in the case of large fleet sizes. In fact, the potential requests for the SAV service are limited. Thus, when the fleet is accessible enough for a major part of potential users, the greater service availability (occurring when the rides are shared) does not necessarily result in an important increase in demand and PKT accordingly. As a result, the growth of PKT and its differences between individual ride and ridesharing scenarios decline.

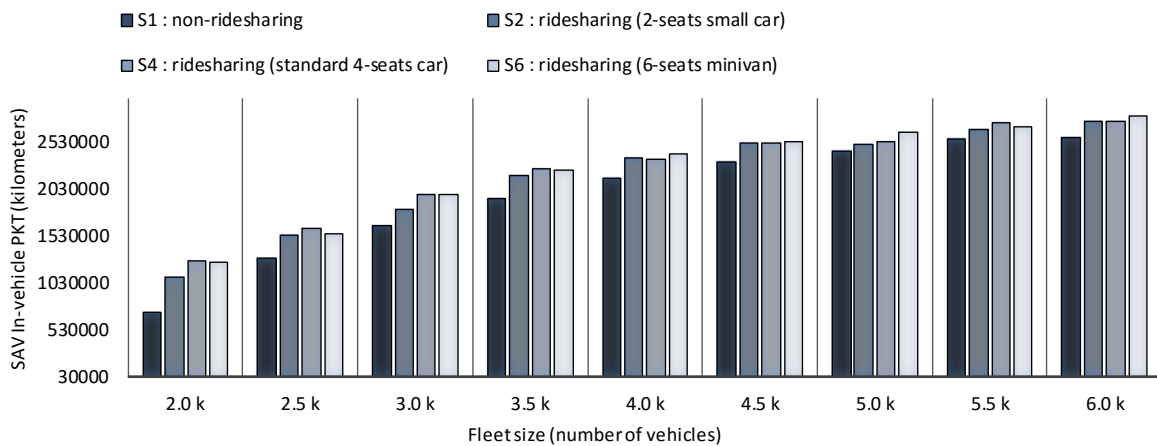


Fig. 4.6. Comparison of SAV overall PKT for all scenarios and fleet sizes.

4.4.4 Vehicle capacity

As mentioned earlier, the best performing fleet size in the case of ridesharing scenarios according to the fleet usage and empty ratios is between 2,500 and 3,500 vehicles. Comparing the PKT for those fleet sizes reveals that the fleet of the standard 4-seats car may be the best performing option for ridesharing. Fig. 4.6 shows that for small fleet sizes, the overall PKT of the standard 4-seats car is greater. In fact, for those fleet sizes, the fleet usage is almost saturated during peak hours (Fig. 4.3). As a result, services are less accessible especially when the vehicle is smaller and the number of available seats is lower. It seems that the service with bigger capacity vehicles would be more used by travelers in that case;

however, due to extra detour time (expected), the PKT of 6-seats SAVs is slightly less than 4-seats SAVs. In other words, for the same SAV service price, users prefer to choose a medium capacity car that has relatively shorter waiting and in-vehicle times compared to a 6-seats minivan. By increasing fleet size, as there is enough SAVs to satisfy the demand, the differences between PKTs for those scenarios become relatively minor. However, since in that case more demand is satisfied, the probability of pooling rides with an acceptable detour time becomes higher. Thus, a limited number of vehicles handle many requests in high demand areas. Meanwhile, the idle vehicles that have already dropped off a passenger far from the demand hubs stay at the same place for a while. This non-homogeneous spatial distribution of idle and high workload SAVs results in a different PKT for ridesharing scenarios with big fleet sizes. This difference occurs when the rebalancing strategy is not enabled. It is of note that in the small and medium fleet sizes, the fleet usage is relatively high and thus, SAVs are somehow rebalanced across the high demand hubs and dispersed better within the region. This shows again the importance of considering rebalancing strategy.

In order to explore the use of vehicle capacities, on-board occupancy rates by the number of passengers (PAX occupancy ratio) are compared for ridesharing scenarios. Fig. 4.7 shows that for all ridesharing scenarios, by increasing the fleet size, the 1 PAX ratio decreases slightly while the other ones increase. In fact, when more vehicles are available, the demand is greater; thus, the probability of finding further trip requests in an acceptable time or distance buffer from the actual ride(s) becomes higher. Therefore, the rides are more shared in the big fleet sizes and more seats are occupied. As illustrated in Fig. 4.7, 3 PAX ratio varies from 5 to 8% in the case of a standard 4-seats car and 6-seats minivan. However, the ratio of 4 PAX is less than 1%. Furthermore, the sixth seat of the minivan is almost never used. Actually, by comparing the other metrics one can observe that the differences between standard 4-seats car and 6-seats minivan are very small. In fact, given the amount of initial investment and operational costs of the bigger vehicles, the extra capacity may not necessarily be profitable. Therefore, it seems that standard 4-seats car is more compatible to the proposed service rather than a 6-seats minivan. Nevertheless, it is important to keep in mind that the extra capacity could have an important impact on SAV's LoS. Furthermore, the 6-seats minivan can also be used for special requirements such as larger groups and families.

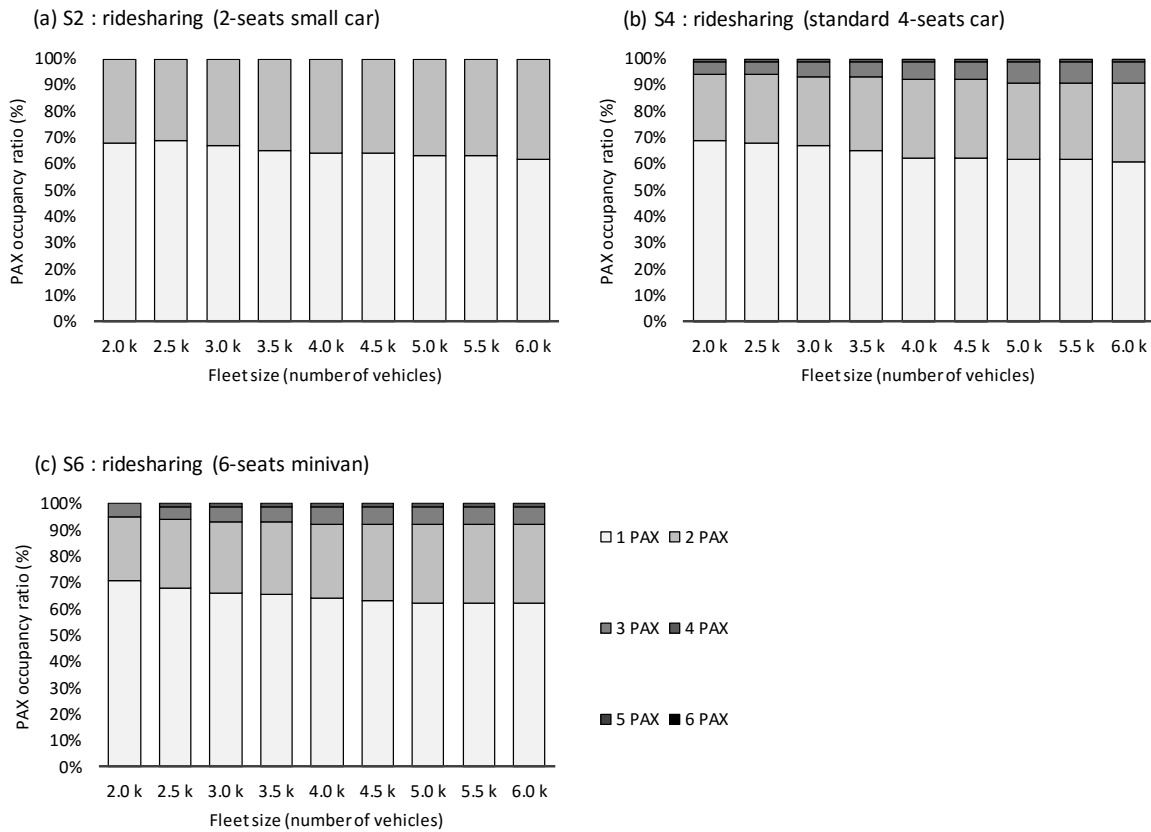


Fig. 4.7. On-board occupancy rates by the number of passenger for ridesharing scenarios.

The analysis on the origin and destination activities of trips performed by a fleet of 3,000 standard 4-seats SAVs (Fig. 4.8) illustrates that almost half of all trips start from or end at users’ homes. For the total of 9% of trips, the purpose at origin or destination is shopping or accompanying (escorting), indicating the importance of extra vehicle capacities in terms of the number of seats or luggage space. Also, given an important share of “Work” and “Study” activities at origin and destination (about 40%), it is likely that providing extra space and additional services for business, entertainment, and education purposes may provide a better customer experience while using SAV service.

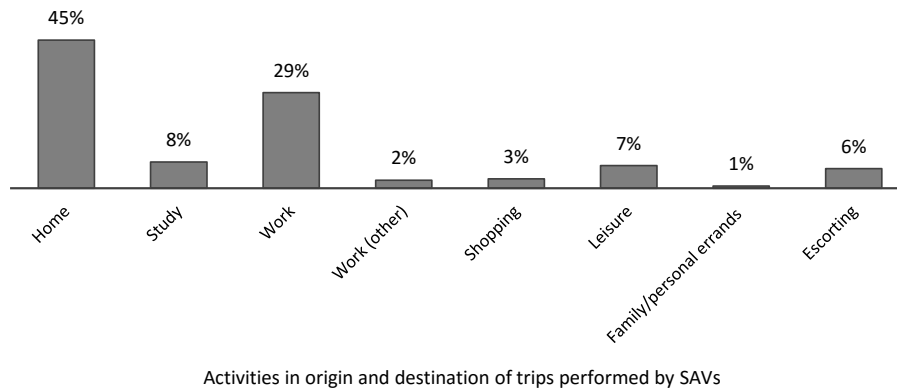


Fig. 4.8. The share of activities in origin and destination of trips performed by a fleet of 3,000 standard 4-seats SAVs (percentage).

4.4.5 Vehicle range

Future SAVs are likely to be electric. In electric vehicles, the range is limited according to the battery capacity and specifications (e.g., weight and life cycle). In fact, given the important cost of battery among vehicles parts, its capacity may strongly affect the capital expenditure and operational expenses. According to the analysis of the SAV range for different scenarios and fleet sizes,

Table 4.5 shows that the average driven distance of SAVs may intensely vary from 361 to 647 km. Furthermore, the vehicles do not have the same driven distance and for some vehicles, the average driven distance could be very long (even 975 km). This occurs when the demand is saturated and the vehicles are occupied for a long time during the day. By comparing the outputs, one can observe that the average driven distance correlates with the fleet usage ratio (Fig. 4.4) and the average number of rides per SAV (Table 4.4). In all fleet sizes, except when 2,000 vehicles are simulated, the average driven distance of non-ridesharing SAVs is the largest compared to other scenarios. This result can be explained by the fact that SAV driven distances are shorter for the case of sharing the ride than when the ride is dedicated just to one passenger. However, in the case of the smallest fleet size, the fleet usage is dramatically lower compared to other fleet sizes due to the high expected waiting time and lower service request (Fig. 4.3). Thus, the average driven distance of non-ridesharing SAVs remains the lowest among all scenarios. The aforementioned distances could further increase by considering vehicle rebalancing, suggesting that vehicle ranges and possibly charging infrastructure need to be taken into account in future research.

Table 4.5

Summary of vehicle average driven distances per simulation day (24 hours) for all scenarios and fleet sizes.

Scenario	Fleet size	2,000	2,500	3,000	3,500	4,000	4,500	5,000	5,500	6,000
S1 - non-ridesharing		414	610	645	647	631	606	566	543	495
S2 - ridesharing (2-seats small car)		469	549	528	543	503	477	422	408	377
S4 - ridesharing (standard 4-seats car)		546	553	546	524	463	445	392	386	354
S6 - ridesharing (6-seats minivan)		541	528	552	526	479	444	408	383	361

4.4.6 Ridesharing service cost

The above-mentioned results are given when the cost of the ridesharing service is assumed to be 20% less than individual rides (0.4 €/km compared to 0.5 €/km for the individual ride). This price is encouraging enough for the travelers to prefer the ridesharing service to individual rides within the same fleet size according to the PKTs (Fig. 4.6). Although reducing service price and sharing rides lead to a higher PKT, the former may not be interesting for the operators as the service benefits for each kilometer of ride decrease, assuming that by an increase in PKT, the fixed cost of operation per kilometer remains unchanged. Thus, it is important to compare the benefit that an operator could gain due to the growth of PKT with the loss that occurs due to the reduction of profit per kilometer. In order to explore the evolution of service performance indicators, two lower prices for ridesharing services are assumed (i.e., 30% and 40% less than individual ride price) and the impacts on PKT and empty vehicle traveling

distance in kilometer (EVK) are compared. Fig. 4.9 shows that reducing service price results in 4-10% higher PKT compared to the initial ridesharing scenario, with the maximum value for 3,000 SAVs in S2 and S4, and 2,500 SAVs in S6. However, the EVK changes vary between -4% and 18% with the maximum values at the same fleet sizes in each scenario. As can be noticed, the reduction of service price does not cause proportionate improvements in the operational performance indicators of the major scenarios and fleet sizes. In fact, the increase of PKT as the main indicator of service profits, which is lower than 10% in the best case, is not enough to cover the loss of direct income occurred due to the lower service price (30-40%). In fact, the latter is certainly higher than 10% since the operational costs are included in the service price. Moreover, in the cases when an important growth of PKT occurs, the EVK increases and therefore the cost of service for operator grows, as well. Hence, for the fleet of 2,500 to 3,500 SAVs, the scenarios with initial service price remain more advantageous.

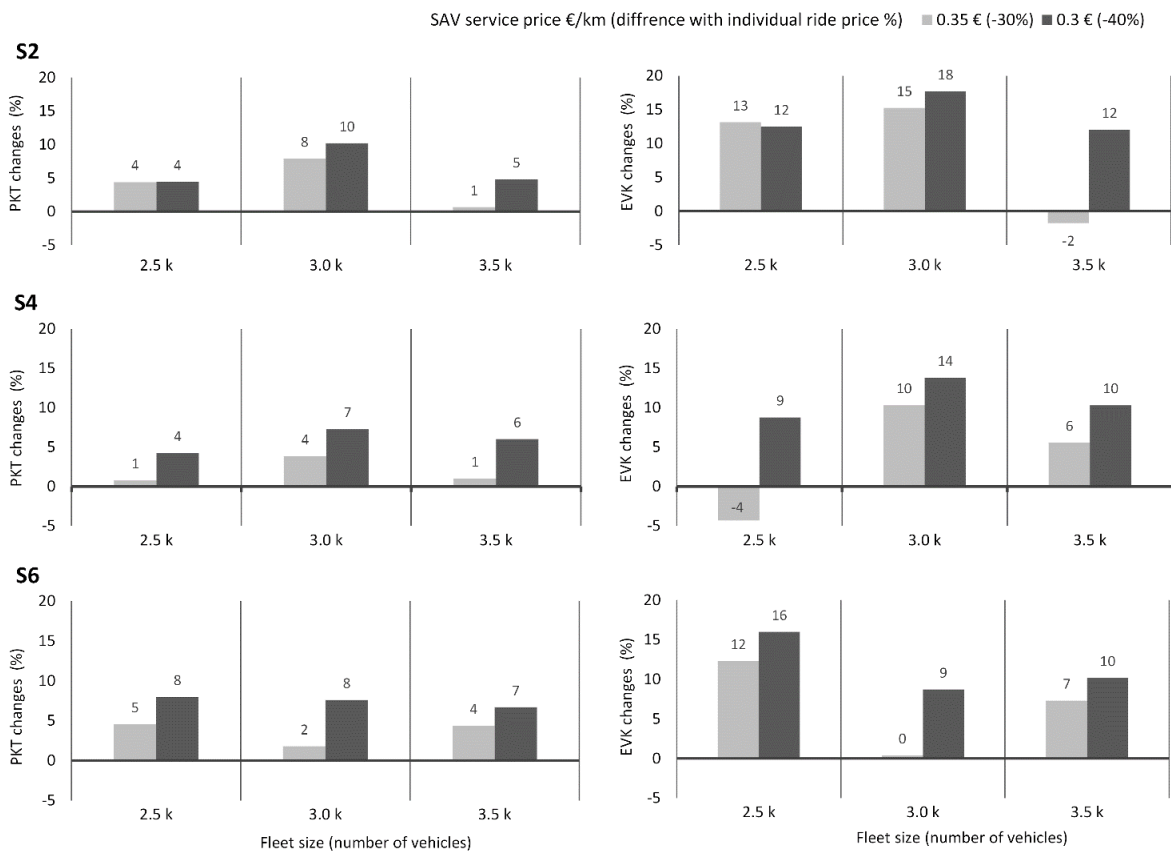


Fig. 4.9. The changes on PKT and EVK in the case of lower prices for ridesharing SAV services of 2,500 to 3,500 vehicles.

The service price has also a dissimilar impact on mode choice decision of different groups of users. In fact, different socio-professional groups have different tradeoffs between time and cost. Thus, by varying the service price, the distribution of users by socio-professional categories changes. To explore these variations, users' groups of ridesharing scenarios are compared assuming a fleet of 3,000 SAVs and different service prices. As can be seen from Fig. 4.10, by decreasing service price, the ratios of "Employed" and "Unemployed" people in all scenarios decrease slightly. Meanwhile, the ratio of "Students" and "People under 14 years of age" increases. As stated before, the cost-related parameters

of mode choice decision are more important than time-related parameters for “Employed” and “Unemployed” people. However, by decreasing service price at this rate, SAVs become less accessible for those groups of users who start their activity in the morning usually after “Students” and “People under 14 years of age” (the activity start time models of the case study area are presented in Chapter 3). As a result, less of “Employed” and “Unemployed” people use the SAV service. The changes in the ratios of “Retired” people and “Homemakers” remain minor.

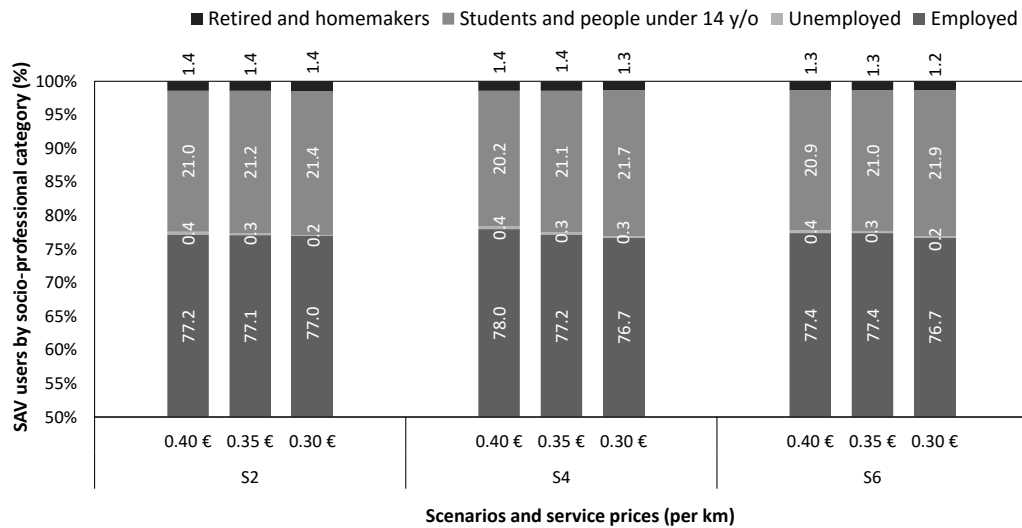


Fig. 4.10. SAV service users by socio-professional category for different service prices in different ridesharing scenarios of 3,000 vehicles.

4.4.7 Rebalancing strategy

The fleet usage ratio and PKT may be improved by rebalancing SAVs. However, enabling this strategy can result in higher EVK. In order to explore the impacts on SAV service performance, the optimum fleet size of each scenario is re-simulated with rebalancing enabled. During these simulations, vehicles are reallocated to different cells with an area of 1 km² (used for demand aggregation) according to the cost flow minimization of idle vehicles and scattered requests. Empty vehicles are considered idle when there is no request after 10 minutes of stay. The reallocation process is done every 5 minutes. The costs of the single ride and ridesharing services are assumed to be as initial values (0.5 €/km for a single ride and 0.4 €/km for ridesharing).

Table 4.6 illustrates the changes in performance metrics. As can be seen, modal share, fleet usage ratio, and in-vehicle PKT increase for all scenarios when SAVs are rebalanced. However, the empty distance ratio increases significantly. In fact, the growth of service benefits that is correlated with fleet usage and in-vehicle PKT occurs at the expense of extra operational costs due to empty traveling distance. Consequently, the decision on using a rebalancing strategy has to be made according to the cost and benefits that the operator of such services expects for each kilometer traveled by empty vehicles and passengers. Some other important changes occur in terms of the SAV’s LoS. Table 4.6 shows that the average waiting time has meaningfully decreased for the ridesharing scenarios after introducing rebalancing. This decrease occurs when the empty vehicles, which are far from the demand hubs, are

reallocated to those zones. As a result, there are more vehicles available within lower waiting times. Nevertheless, in-vehicle and detour times remain almost unchanged. Regarding in-vehicle time, the changes before and after introducing rebalancing strategy are minor since the trip patterns do not change significantly. Consequently, this indicator varies in the same order observed for various fleet sizes of the same scenario (Fig. 4.2). However, given the greater number of available vehicles and accordingly lower waiting times, it seems that the detour time should similarly decrease. This decrease did not occur due to the higher demand as well as lower 1 PAX and bigger 2 and 3 PAX ratios. In fact, after enabling rebalancing, more rides are shared. Therefore, the average detour time remains almost unchanged. In the case of the individual ride scenario, since the service is saturated during morning and evening peak hours, the rebalancing strategy does not necessarily result in significant waiting time changes.

Similar to fleet usage and in-vehicle PKT, average driven distances increase for all scenarios. In other words, by introducing a rebalancing strategy the vehicles need to have larger batteries or need to recharge more frequently.

Table 4.6

Performance metrics' changes before and after enabling the rebalancing strategy.

Scenario	S1-non ridesharing (3,500 SAVs)		S2- ridesharing (2,500 2-seats SAVs)		S4-ridesharing (3,000 4-seats SAVs)		S6-ridesharing (3,000 6-seats SAVs)	
	no rebalancing	with rebalancing	no rebalancing	with rebalancing	no rebalancing	with rebalancing	no rebalancing	with rebalancing
SAV modal share (%)	6.0	6.3	4.6	5.2	5.3	6.4	5.4	6.4
Average waiting time (min)	18.5	18.4	18.9	13.9	20.7	13.1	21.1	14.8
Average in-vehicle time (min)	38.5	38.7	43.9	44.1	46.0	45.2	46.0	44.8
Average detour time (min)	N/A	N/A	4.7	5.2	6.1	5.8	6.0	5.9
Fleet usage ratio (%)	59	68	50	66	50	66	51	67
Empty distance ratio (%)	14	20	14	26	15	24	16	24
In-vehicle PKT (km)	1.93 M	2.08 M	1.53 M	1.81 M	1.97 M	2.40 M	1.97 M	2.41 M
1 PAX ratio (%)	100	100	69	63	67	59	66	61
2 PAX ratio (%)	N/A	N/A	31	37	26	33	27	31
3 PAX ratio (%)	N/A	N/A	N/A	N/A	6	7	6	7
4 PAX ratio (%)	N/A	N/A	N/A	N/A	1	1	1	1
5 PAX ratio (%)	N/A	N/A	N/A	N/A	N/A	N/A	<1	<1
6 PAX ratio (%)	N/A	N/A	N/A	N/A	N/A	N/A	0	0
Average driven distance (km)	647	746	549	715	546	707	552	723
Max. driven distance (km)	894	978	880	964	866	896	888	939

4.5 Discussion and conclusion

The rising popularity of carsharing and technological advancements on electric and autonomous vehicles has led to the emergence of new shared mobility systems. Some car manufacturers and transportation network companies (e.g., Uber and Lyft) have already announced their plans for deploying SAVs in the future. Understanding dynamic tradeoffs between service configuration and demand is an important prerequisite for delivering such services. This chapter sought to investigate the design of an SAV service considering its demands responsive to the network, user taste variations, and traffic in a multimodal context. Simulations of various SAV fleet sizes and capacities considering ridesharing and rebalancing strategies across the Rouen Normandie provide initial insights. As suggested by these simulations, the SAVs performance is strongly correlated with the fleet size, specifically in the case of individual ride service. The results show that the SAV modal shares vary from 3.1% to 7.6% for different fleet sizes of 2,000 to 6,000 vehicles. While the SAV modal share of small fleet size for the individual ride is the minimum among all scenarios including ridesharing with various vehicle capacities, this term is the greatest for the medium and big fleet sizes. The latter actually occurs when the fleet of individual ride service exceeds a critical size (i.e., 2,500 SAVs), from which the smaller fleet size results in a significant decline of fleet usage (i.e., 34% compared to 8% that is observed from 3,000 to 2,500 vehicles). In fact, for fleet sizes this small, the expected waiting times increase meaningfully and lead to very low service utility compared to other alternatives; and the demand decreases, accordingly. On the contrary, once the peak hour demand is satisfied in an acceptable waiting time, the service performance decreases slightly by increasing fleet size. This variation is not as significant as in ridesharing scenarios where the change of fleet size has less important impacts on the LoS. The results also suggest that the average waiting time, which is estimated when the interaction of demand and supply is relaxed (and therefore it is different from the aforementioned expected waiting time), decreases meaningfully for the smallest fleet sizes. This decrease is actually contrary to what is usually suggested when the SAV simulation with predefined or static demand is performed and shows the importance of considering dynamic demand in the simulation of on-demand services.

Further analysis reveals that in the case of ridesharing services without vehicle rebalancing, the changes in average waiting time remain insignificant for the medium and big fleet sizes. Nevertheless, this indicator decreases in the individual ride service for the big fleet sizes. In fact, in ridesharing scenarios since the service is never saturated in the case of medium and big fleet sizes, when an upcoming request is registered, the nearest vehicle with available seats is allocated to it. However, in individual ride services, the nearest empty vehicle has to be allocated to that request. Bigger fleet sizes result in a large number of vehicles available in individual ride services and the waiting time decreases accordingly. The increase in fleet size similarly results in more available seats in ridesharing scenarios (up to 5%). However, this change is not significant since the fleets are not as occupied as in individual ride scenario and the increase in seat availability does not have an important impact on the availability of service. It is also shown that average in-vehicle and detour times vary slightly according to the fleet size. These changes are relatively minor (less than 4 minutes) and follow almost the same trend.

By comparing the fleet usages and empty distance ratios of different scenarios, it is found that the optimum fleet sizes for the individual ride and ridesharing cases are different. These results suggest that

while the best fleet size of individual rides is 3,500 SAVs, in the case of a small car with two seats, 2,500 vehicles and for standard 4-seats car and 6-seats minivan, 3,000 vehicles are the best performing fleet sizes. Based on the obtained results, considering transport-related service performance, there are no big differences between standard 4-seats car and 6-seats minivan. Since the bigger capacity vehicle may be financially less efficient due to the higher vehicle and operational costs, it seems that 6-seats minivan cannot be a performant alternative. Nevertheless, it is important to bear in mind that the extra capacity and seats may potentially affect the user comfort perception and consequently their choice in the real-world. Further comparison of four suggested fleet sizes illustrates that given the relatively high in-vehicle PKT and low empty distance ratio of the 3,000 vehicles with share rides, this scenario is the best option among all the considered scenarios. Furthermore, taking into account the trade-off between waiting and detour times and service cost, we consider that the proposed pricing scheme for SAV ridesharing service (20% less compared to individual ride) is attractive enough for users. In addition, the results show that a decrease in ridesharing service prices up to 40% of the individual ride does not cause proportionate improvements on the operational performance indicators and is not beneficial for the operator.

Importantly, enabling vehicle rebalancing is found to have a profound effect on both user and service-related metrics. For optimum fleet sizes of ridesharing scenarios, rebalancing leads to shorter average waiting times (i.e., 25-35%). However, in individual ride scenario, this indicator remains unchanged since the service is already saturated in peak hours without enabling rebalancing. Although in-vehicle PKT and empty distance ratio increase for all scenarios, the change in the latter indicator is relatively more important (i.e., 42-85% against 7-17%). Besides, the detour times remain almost unchanged. Given these indicators, the decision on enabling rebalancing strategy should be made according to the financial analysis based on the cost and benefits that operator of such services expects for each kilometer traveled by passengers and empty vehicles.

The detailed service usage indicator estimated for 1-h time slices illustrates a shift of the morning peak-hour service usage from 7-9 a.m. for the small fleet sizes to 8-10 a.m. for big fleet sizes. This result indicates the effect that different SAV users with different trip patterns and taste variation may have on the service usage and prove the importance of considering that user differentiations in SAV demand modeling and simulation.

A further analysis on the vehicle replacement rates, which indicate how many cars can be removed by providing SAVs, shows that only a maximum of 3.5% of travelers drop their private cars entirely. This results in at most the reduction of 1.7% private cars and SAVs together in the network. Estimated values are consistent with the modal shifts from car to SAV for the case study of this thesis (that is maximum 1.8%), and they are much less optimistic than those estimated in other studies. These results emphasize again the importance of considering dynamic demand and a multimodal network in the simulation and impact estimation of future SAVs.

Finally, the average driven distances for optimum scenarios without rebalancing varies from 546 to 647 km. Assuming a fleet of electric SAVs, given the relatively lower range of today's electric vehicles, it will be necessary to recharge the majority of vehicles during the day. Furthermore, enabling rebalancing leads to longer average traveled distance (i.e., 707 to 746 km). These indicators show that vehicle ranges and charging infrastructure need to be carefully taken into account in future research. In the next chapter, electric SAVs (SAEVs) are integrated into the simulation and the evolution of service

performance indicators according to various charging station positioning and vehicle ranges are evaluated.

Chapter 5

Shared Autonomous Electric Vehicle and Charging Infrastructure

The majority of future SAVs will most probably be electric. It is therefore important to understand how limited vehicle range and the configuration of charging infrastructure will affect the performance of shared autonomous electric vehicle (SAEV) services. This chapter aims to explore the impacts of charging station placement, charging type (rapid charging, battery swapping) as well as vehicle range onto service efficiency and customer experience in terms of service availability and response time.

5.1 Introduction

AVs have strong potential to complement on-demand mobility services such as app-based cabs, carsharing, and ridesharing (Greenblatt and Shaheen, 2015), and can merge these systems into a single transportation mode. Simultaneously, electric vehicle (EV) production continues its expansion to encourage reducing local pollutant emissions. Given important advances in battery technologies for EVs in recent years and the growing deployment of policy for achieving a shift toward electric and green transportation, these vehicles are forecasted to make up to as much as 30% of global auto production by 2030 (International Energy Agency., 2018). Considering these parallel evolutions, it is very likely that future SAVs, as a major part of current AV concepts, will mainly be powered by electricity. There are many reasons that make future SAVs likely to be electric. First, the price of EV technology continues to fall and they become financially advantageous in comparison to vehicles with combustion engines (Berckmans et al., 2017; Nykvist and Nilsson, 2015). Second, EVs are best suited to reduce emissions in the sector and therefore help meet policy targets. Specifically in this case, it is suggested that autonomous EVs produce dramatically less emission than gasoline AVs (Gawron et al., 2018) and consume less energy (Vahidi and Sciarretta, 2018). Third, for longer daily travel distances experienced by shared fleets, EVs are technically and economically more beneficial in terms of maintenance needs (Logtenberg et al., 2018; Palmer et al., 2018; Weldon et al., 2018). However, despite the aforementioned advantages, the configuration of a shared service based on EVs meets some operational concerns. Owing to the limited battery capacities and the lengthy charging process, a shared autonomous electric vehicle (SAEV) system may not achieve the same service usage compared to a non-electric SAV system. Besides, providing charging stations can be very costly, specifically in the congested and high-density areas. Furthermore, charging outlets at each station are limited according to the available space and charging power, and can only be used for a small part of a fleet at a time. Hence, SAEVs' specification and charging station configuration must be carefully adjusted to meet the optimum service efficiency. It is important to note that the infrastructure needed for SAEVs may be substantially different from ordinary EVs (Weiss et al., 2017). Importantly, SAEV fleets could have a significant demand for rapid charging, potentially at high service demand areas and peak hours. Moreover, given the fastest charging rates provided by today's commercially available level 3 chargers, it seems that a part of SAEV fleet will be unavailable for at least a few tens of minutes per vehicle and per charge. This decrease in service availability may result in higher traveler waiting times and, consequently, less demand and vehicle utilization. Therefore, charging processes must be wisely scheduled to meet users' maximum demand.

The SAEV vehicle specification (i.e., battery capacity or vehicle range) and the configuration of required infrastructure including the charging station placement, charging speeds, and available spaces in charging stations could certainly affect service performance. These aspects have attracted less attention particularly when such services are simulated employing more sophisticated demand modeling and especially multimodal dynamic-demand approaches. The purpose of this chapter is to provide new insight into the design of SAEVs by exploring how the service configuration could affect its effectiveness. With this aim, this chapter makes four major contributions.

- First, different strategies of charging station placement are proposed and compared by employing a set of service and user-related performance metrics. These strategies are based on two different optimization models.

- Second, the service performance according to vehicle/outlet ratio is evaluated.
- Third, the application of battery swapping station (BSS) for SAEV services is investigated for the first time.
- Finally, a real-world case study, based on the population and trip patterns of the Rouen Normandie is employed to demonstrate impacts of charging infrastructure and SAEV battery capacity on the service performance and its effectiveness.

To perform these investigations, the modeling and simulation framework, proposed in Chapter 2, is used. The simulations incorporate dynamic traffic assignment in which SAEV mode choice is integrated into multimodal travel demand patterns according to user taste variations.

The remainder of this chapter is structured as follows. Section 5.2 presents an overview of the related work on this topic. Section 5.3 describes the methodology and model specifications, which includes the multi-agent transport model, charging stations' placement algorithms, scenarios and evaluation criteria. Section 5.4 discusses the results of the simulations for the case study. Finally, Section 0 presents conclusions from the analytical framework and case study results and provides suggestions for further work.

5.2 Prior research

Simulating SAV services and analyzing fleet performance in terms of passenger access times, vehicle mileage and empty distances, and occupancy rates have been performed in several previous research efforts. Limited attention, however, has been given to the SAEV fleets. Particularly, a major part of nowadays investigations is dedicated to the optimization of SAEV infrastructure in which the demand is assumed to be deterministic. In one of the first efforts, Chen et al. (2016) tried to examine the operation of non-ridesharing SAEVs under various vehicle range and charging time scenarios for the case study of Austin, applying an agent-based simulation built from a former study (Fagnant and Kockelman, 2014). This investigation is based on a spatially aggregated demand model in which no traffic assignment and network loading take place. To determine the number of charging stations and the required fleet, passenger access times are integrated into the model and it is assumed that the requests with waiting times exceeding 30 minutes are eliminated. Once the charging stations and the initial fleet size are determined according to the greedy algorithm, different scenarios with four vehicle ranges and two recharging times are simulated. The simulation results show significant impacts of charging infrastructure and vehicle range on fleet size. It is also suggested that additional vehicle mileages due to accessing charging stations remain less than 5%, with the worst case for the minimum vehicle range and rapid charge scenario. In this study, for each scenario, a different number of charging outlets in the stations is presumed. Considering the size of the fleet, a wide range of vehicle/outlet ratio (1.6~13.7) is implicitly assumed. This ratio denotes the number of vehicles per electric vehicle supply equipment (EVSE). As this variation is not applied to similar scenarios, no conclusion on the impacts of charging space on SAEV service performance could be provided. Based on the mentioned study, Farhan and Chen (2018) made an effort to evaluate the performance of SAEVs for a ridesharing service. In the extended simulations, a model of rideshare matching optimization is proposed to determine optimal routes to pick up and drop off multiple travelers within a given time interval. Two vehicle ranges (short and long) and charging speeds along with four vehicle capacities are assumed for the SAEV fleet.

According to their results, enabling ridesharing strategy leads to a smaller fleet size and a lower number of required charging stations. By switching from individual ride to ridesharing, they realized that the greatest change occurred when the second passenger is allowed to the vehicle. In ITF (2015), an agent-based model relying on a static representation of the traffic environment is applied to simulate a citywide implementation of SAVs. This study covers scenarios that are more diverse and includes SAEVs. Based on their results, it is inferred that by assuming a fleet of fully electric vehicles equipped with rapid charging batteries (30 minutes) and a range of 175 km, the change on required fleet size compared to non-electric SAV is minimal (+2%). Iacobucci et al. (2019) focused on optimization of SAEV operations upon the transportation network of Tokyo considering charge scheduling and vehicle-to-grid based on the stochastic demand and simplified time-varying traffic. The employed optimization includes minimization of waiting times and charging costs incorporating dynamic electricity pricing. Their simulation results reveal that although the proposed charging optimization reduces the cost of charging down to 10%, traveler waiting times are not significantly affected. The study, however, assumed that charging outlets are always available and therefore there are no impacts on service availability and traveler waiting time. Kang et al. (2016) developed a system design and decision framework for SAEV fleet assignment, charging station placement, and powertrain design. Their proposed service design process is based on a system-level profit-maximization problem according to a long list of operational and demand-related decision variables, which aims to maximize operating profit. The framework consists of four subsystem models, two of which focusing on fleet assignment by minimizing traveler waiting time and charging station placement by minimizing the distance between SAEVs and charging stations. The demand in the mentioned study is however estimated using a marketing approach, which is not responsive to the transportation network and available modes. While the impact of waiting time on mode choice decision of travelers is neglected in this study, the authors conclude that the proposed decision framework results in lower traveler waiting time. Bauer et al. (2018) used an agent-based model and analyzed the cost, energy, and environmental implications of SAEV service operating in Manhattan. An iterative process was employed to optimize the positioning of charging stations by starting with charging stations of one EVSE outlet unit everywhere and eliminating at each iteration the least used chargers. They found the optimal battery size and number of charging stations to minimize costs through sensitivity analysis. They estimated that SAEV costs would be the lowest with a battery range of 50-90 miles, with either 66 chargers of 11 kW and 44 chargers of 22 kW per square mile. They also concluded that currently available EV ranges would be more than sufficient, and reducing battery range from current levels could result in significant cost savings. Nevertheless, because their results are based on a static demand that is built from cab trips in New York City, they may not reflect the real usage pattern of a DRT system.

While the mentioned studies incorporate predefined demands, there are some other investigations that benefit from a dynamic demand, responsive to the network or/and traffic. Loeb et al. (2018) applied a tour-based model coupled with a widely used multi-agent transport simulation platform (MATSim) to anticipate the required charging stations as well as their sizes and positions, assuming a fleet of SAEVs serving travelers across the Austin. The main core of this research is similar to that Chen et al. (2016), except that a more realistic demand, responsive to traffic, is used. A set of scenarios including various charging times, fleet sizes, vehicle ranges and different numbers of charging stations are simulated. Authors conclude that the number of required stations is highly dependent on vehicle range. However,

their simulation results suggest that the number of stations is not sensitive to the fleet sizes and charging times. It is also indicated that the faster charging times, when charge times are shorter than 120 min, and longer vehicle ranges (above 175 km) do not essentially improve user waiting time. The same authors in a more recent work added gasoline hybrid-electric vehicle to the SAV and SAEV fleet alternatives and compared the performance of proposed service according to the user response time and financial analysis (Loeb and Kockelman, 2019). To make the demand more realistic, they revised the assumption of maximum accepted waiting time and attributed it to a probability graph. The authors investigated a different set of scenarios compared to their previous study, and found that the fleet of long-range (200 miles) SAEVs with rapid charging (30 minutes) equipment is the most profitable scenario among the fully electric fleets. Moreover, they concluded that a fleet of gasoline hybrid-electric vehicle outperforms the fully electric vehicles. Table 5.1 shows a summary of the aforementioned studies and states the methodology of demand modeling, traffic simulation, and the main features.

Table 5.1

Summary of the selected literature on SAEV service simulation with focus on methodology and main features.

Author(s), year	Demand / Network traffic	Charging station placement	Vehicle/EVSE outlet ratio	Battery capacity- vehicle range	Charging speed- grid connection
Chen et al., (2016)	Given / static	Greedy algorithm	1.9/2.4/2.5/13.3 ^a	64/80/160/200 (mi)	30/240 (min)
Farhan and Chen, (2018)	Given / static	Greedy algorithm	NM	80/190 (mi)	45/240 (min)
ITF, (2015)	Dynamic / static	NM	NM	175 (km)	30 (min)
Iacobucci et al., (2019)	Given / time-varying	NM	NM	50 (kWh)	20/50 (kW)
Kang et al., (2016)	Marketing / static	P-median model	8.0 (optimal sc.)	44.8 (kWh)	56 (min)
Bauer et al., (2018)	Given / static	Elimination method	2.8-3.3/6.5/32.5 ^a	10-200 (mi)	7/11/22/50 (kW)
Loeb et al., (2018)	Dynamic / dynamic	Greedy algorithm	NM	100-325 (km)	0-240 (min)
Loeb and Kockelman, (2019)	Dynamic / dynamic	Greedy algorithm	NM	60/200 (mi)	30/240 (min)

^a Estimated based on the data provided by each study.

Table 5.1 shows that most of earlier approaches investigating the operation of SAEV service are based on the predefined or simplified demand and static network traffic except for the Loeb et al. (2018) and Loeb and Kockelman (2019), both of which limit the SAEV mode choice decision with a maximum waiting time or trip distance rate. This indicates that in the mode choice mechanism, the level of services for SAEV and other alternatives are ignored. The results obtained from Chapter 4 demonstrate that by considering dynamic demands, the service usage changes significantly according to the service configuration (Vosooghi et al., 2019b). In the case of SAEV with limited range, the service is relatively less available. It is, therefore, necessary to take into account the demand that is dynamically responsive to the network and available alternatives. The charging station placement and its impacts on SAEV service performance also remain missing in all of the prior studies. Given the cost of providing such infrastructure, especially in the high-density areas, the charging station placement resulting in a different operational metrics can certainly affects the profits. Furthermore, even if most of aforementioned investigations incorporate financial analysis, the variation of EVSE outlet ratio, which is another important parameter on the infrastructure cost estimations, is still omitted.

5.3 Model specification and set-up

5.3.1 Simulation framework

The present work is based on our previous investigation of non-electric SAV service design (Chapter 4) where the proposed framework of modeling and simulation, presented in Chapter 2 is employed. To simulate SAEVs, the electric vehicle extension proposed by Bischoff et al. (2019) is used as well. The availability of micro-data is essential for the multi-agent activity-based simulation. In particular, to achieve the proper fine-grained model, it is necessary to input details of the individual and household characteristics, as well as locations of home, work and other activities for the entire population of the study area. For this purpose, the synthetic population of the case study area is generated using fitness-based synthesizing with multilevel controls developed previously (Chapter 3). Activity chains are extracted from a recent transport survey (EMD Métropole Rouen Normandie 2017) and an analysis of population census data (INSEE 2014), and are allocated to each individual of the synthetic population. The transportation system of the case study is first simulated, and then the simulation is calibrated according to the actual modal splits. Next, the SAEV mode and its users' taste variations in terms of mode choice (Chapter 3) and a local survey (Chapter 2) are integrated into the model. In order to allocate the SAEVs more efficiently, a dispatching algorithm developed by Bischoff and Maciejewski (2016) is used. The vehicle dispatch algorithms are slightly adapted taking into account the vehicle's state of charge (SoC) when assigning it to a passenger. Therefore, a vehicle can only be dispatched if its SoC is sufficient to complete the trip and reach a charging station. Vehicles are sent to nearby charging stations with available charging capacity. When no charger is available, the vehicle is queued at the closest charger until a spot becomes available. This is an extension of a heuristic originally developed in Bischoff and Maciejewski (2014).

The passenger waiting time without any limitation on maximum acceptance value is also integrated into the mode choice model incorporated in the proposed framework of modeling and simulation. Because the demand is dynamically responsive to the network and traffic, this simulation produces a more accurate estimation of SAEVs service demand compared to the reviewed studies mentioned in

Table 5.1. Furthermore, the simulation is performed in the multimodal network in which users can choose other modes if SAEVs are not available in relatively acceptable access times and cost. It is important to underline that due to the high computational time, the population of the case study area has been downscaled to 10% and the network capacity has been modified in the performed simulations. By this rate of downscaling, quite accurate outputs can be provided compared to the full-scale model (Bischoff and Maciejewski, 2016b).

Since a full optimization process regarding the charging station positions using agent-based simulation is computationally expensive, we propose to generate charging station locations in a separate model as a first step.

5.3.2 Charging station placement

The first part of the SAEV simulation generates a base set of charging stations. For this purpose, two modeling approaches are employed: (i) maximizing coverage of charging stations by considering the potential pick-up and drop-off locations and (ii) minimizing distances between those locations and charging stations. A third strategy of charging station placement, based on the second model, avoids placing charging stations in areas with low parking availability. These three strategies of charging station placement are compared by a set of performance indicators. The data used for identifying potential pick-up and drop-off locations are based on the non-electric SAV users' demands, which have already been estimated in Chapter 4. The SAV user pick-up locations are used because their dispersion determines areas with high potential demand. If the charging stations are located in those areas, SAEVs that have finished charging would be closer to demand locations, potentially resulting in lower passenger waiting times. Similarly, SAEVs that need charging are likely to be closer to charging stations after having dropped off users. Therefore, by considering the start and end locations of potential trips, we aim at minimizing the access distance to the charging stations and requests. In order to perform the optimization process, those locations are aggregated to the predefined cells. The following two optimization models are used to compute charging station locations.

The first optimization problem is inspired by Asamer et al. (2016) who tried to find charging station locations for urban electric cabs through maximal covering location problem (MCLP) (Church and ReVelle, 1974). For this purpose, the case study area is meshed to a set of cells C . For each cell, a value of $c_i, i \in C$ counting the SAV pick-up and drop-off locations within the cell is assigned. Moreover, the cells that have a direct connection to the cell $i \in C$ are denoted as a set of neighbors $N_i \subseteq C \setminus \{i\}$. If the cell i is selected for placing a charging station, a direct coverage weight of $w_0: 1$ is assigned to it. Otherwise, its weight is equal to zero. If at least one of its neighbor cells is selected for the charging station placement, a neighbor coverage weight of $w_1: 0.5$ is set to the cell. Otherwise, the neighbor coverage weight is set to zero. The number of charging stations is limited by P . The aim is to maximize the sum of covered pick-up and drop-off locations' counts, whereas the sum of direct and neighbor coverage weights for each cell remains less or equal to one. This means that if a cell is selected for placing a charging station, the neighboring cells may not have a charging station inside. Hence, that avoids to place charging stations near to each other while they are kept enough dispersed. The model can be written as the following mixed integer program:

$$\max \sum_{i \in C} c_i x_i \quad (5.1)$$

subject to

$$\sum_{i \in C} y_i \leq P \quad (5.2)$$

$$x_i \leq w_0 y_i + \sum_{j \in N_i} w_1 y_j \quad \forall i \in C \quad (5.3)$$

$$x_i \in \{0, 0.5, 1\} \quad \forall i \in C \quad (5.4)$$

$$y_i \in \{0, 1\} \quad \forall i \in C \quad (5.5)$$

where x_i represents the sum of direct and neighbor coverage weights. Binary variable y_i decides if a charging station is located in cell i or not.

Since the neighbor coverage weighting is not adequately indicative for our optimization goal especially in terms of distances, a second model, based on the distance between charging stations locations and the center of cells, is proposed. This model is based on warehouse allocation problems (P-Median), which has already been applied by Kang et al. (2016) to determine optimal charging station locations in Ann Arbor, Michigan case study. A similar partition of cells C was used as in the previous problem. Cells' centroids E are determined as a set of candidate positions of charging stations. The number of charging stations to locate is determined by P . Similar to the previous model, for each cell's centroid, a value of c_i , $i \in C$ counting the SAV pick-up and drop-off locations within the cell is assigned. The distance between centralized counting of cell centroid i and candidate location for charging station (i.e., centroid j) is defined by d_{ij} . The objective here is to minimize the counting-weighted distance of pick-up or drop-off locations and charging stations, expressed as the following mixed integer program:

$$\min \sum_{i \in C} \sum_{j \in E} c_i d_{ij} x_{ij} \quad (5.6)$$

subject to

$$\sum_{j \in E} x_{ij} = 1 \quad (5.7)$$

$$\sum_{j \in E} y_j = P \quad (5.8)$$

$$x_{ij} \leq y_j \quad \forall i \in C, \forall j \in E \quad (5.9)$$

$$y_j \in \{0, 1\} \quad \forall j \in E \quad (5.10)$$

$$x_{ij} \in \{0, 1\} \quad \forall i \in C, \forall j \in E \quad (5.11)$$

where x_{ij} is the binary variable that decides if centroid i is satisfied by charging station located in the cell j and makes sure that each centroid is served by exactly one charging station. Binary variable y_i decides if a charging station is located in the cell j or not.

5.3.3 Simulated scenarios

Different scenarios are simulated to examine the operation of SAEVs in Rouen Normandie under various charging and battery swapping station placements, types of charging outlets (in terms of charging speed), number of charging units per station (vehicle/EVSE outlet ratios), and SAEV battery capacities. Rouen Normandie was chosen since experiments on electric and shared self-driving cars are currently undertaken, and a comprehensive travel survey is recently made for this region; as a result, the access to some essential data was provided. Rouen Normandie is formed of several cities, peri-urban and rural areas, and includes about 484,000 inhabitants and 231,000 households performing 1.5 million trips on average per day. Private car, walk, and public transport with respective modal splits of 43.6%, 29.3%, 11.4%, are the main modes used for traveling in this area (Cerema, 2017).

The simulated scenarios are grouped by the optimization strategies that have been used for locating charging and battery swapping stations. To compare and evaluate the scenarios, a set of performance metrics for SAEV service, infrastructure, and users are defined. In all scenarios, a fleet of 3,000 standard 4-seats SAEVs is integrated into the simulation. This number of vehicles as the best fleet size of non-electric SAV service with ridesharing is obtained from Chapter 4. In the simulations, SAEVs are initially allocated to the first requests from four main depots located homogeneously across the case study area. Since the purpose of this chapter to explore the impact of charging station placement, these depots are considered as not used for charging or battery swapping during simulations. According to the size of the case study area, the maximum number of stations is assumed to be limited to 12. The SAEVs are sent to charging or battery swapping stations once the battery capacity is below 20% or when the trip distance for the next request (by prediction) shows that with the actual SoC the task could not be undertaken. The vehicle battery capacities are parameterized according to the Renault Zoe specifications; i.e., 41 kWh and 50 kWh for Zoe R110 and Zoe second-generation, respectively (Renault Zoe technical sheet, 2019). The autonomous version of this car is, at the time of writing this dissertation, being used for real experimentation in Rouen Normandie. The charging speeds are considered correspond to available and provided supply equipment; i.e., 22 kW in the case of the normal charger and 43 kW for a rapid charger (Renault Zoe technical sheet, 2019). It is also considered that SAEVs stay at charging stations equipped with normal chargers until the full charge state is reached. However, rapid chargers charge up to 80% of battery capacity and then the SAEVs leave the charging stations. SAEVs are discharged based on the energy consumption model (Ohde et al., 2016), which was set up in this thesis according to the specifications of Renault Zoe. By employing this model, the energy consumption is estimated according to the basic vehicle parameters (i.e., vehicle mass, drag coefficients), acceleration and deceleration rates, and the average speed driven on links (road sections), rather than assuming fixed km/kWh. It should be mentioned that performed simulations do not consider the pre-emptive charging.

The price of the service is assumed as 0.4 €/km for all scenarios. The distance for calculating service price is considered as the distance from a pick-up point to destination excluding detour distances. The assumed service price is slightly more expensive than private car ride costs in France (0.3 €/km - DG Trésor (2018)). However, this assumption is similar to the values that have been estimated or concluded in other investigations. For example, Chen et al. (2016) estimated the price for electric SAV from \$0.66 to \$0.74 per person-trip-mile (about 0.36-0.40 €/km) accounting all costs and operating margins, and Bösch et al. (2018) estimated it 0.43 CHF per passenger kilometer (0.39 €/km).

5.3.4 Performance metrics

A set of performance metrics was used to evaluate and compare the scenarios. The term “fleet usage ratio” is used to evaluate the overall performance of a fleet. This indicator is defined as the number of occupied or in-service vehicles (including going to pick up a client) over the number of all vehicles. The “vehicle kilometers traveled (VKT)” indicator shows the total distance that each vehicle travels. The “empty distance ratio”, representing the proportion of extra VKT (due pick-up and recharging trips) over total VKT, was used to evaluate empty vehicle traveling distances. The average waiting and in-vehicle times are the terms that represent the time that a traveler spends waiting for a vehicle and for reaching its destination inside the vehicle. The “average detour time” shows extra travel time due to the shared rides. In order to compare the service revenues for different scenarios, the “in-vehicle passenger kilometer traveled (PKT)” is defined. This indicator presents the sum of trip distances traveled by each individual in SAEVs. In order to investigate the impact of charging infrastructure on the usage pattern of SAEV service, the “PAX occupancy ratio” is proposed. This term shows the average occupancy rates of SAEVs according to different numbers of passengers being simultaneously on-board. The “total plug-in time” is the sum of the times that SAEVs are plugged in charging stations. The “total queue time” is estimated as the sum of the times that SAEVs queued at the charging stations until spots become available. Mode shares were compared to evaluate the overall performance of SAEV service in the transportation system.

5.4 Case study results

5.4.1 Base-case scenario

A base-case scenario simulation run was conducted without considering any vehicle range limitation (non-electric SAV). Table 5.2 illustrates the service, user, and network-related indicators. As can be seen, the fleet of non-electric SAVs forms 5.3% of modal shares. On average, 50% of vehicles are in-use mode during a given day simulation. The in-use mode includes times when vehicles are going to pick up a client. The empty distance traveled with that purpose presents on average 15% of overall VKT. The PKT goes up to 1.97 million kilometers in the base-case scenario. Estimated PAX occupancy ratios show that 67% of VKT has been with the only one passenger on-board. The average SAV driven distance is estimated at about 546 km. This indicator suggests that future SAVs with present EV ranges will necessarily require to recharge during the day.

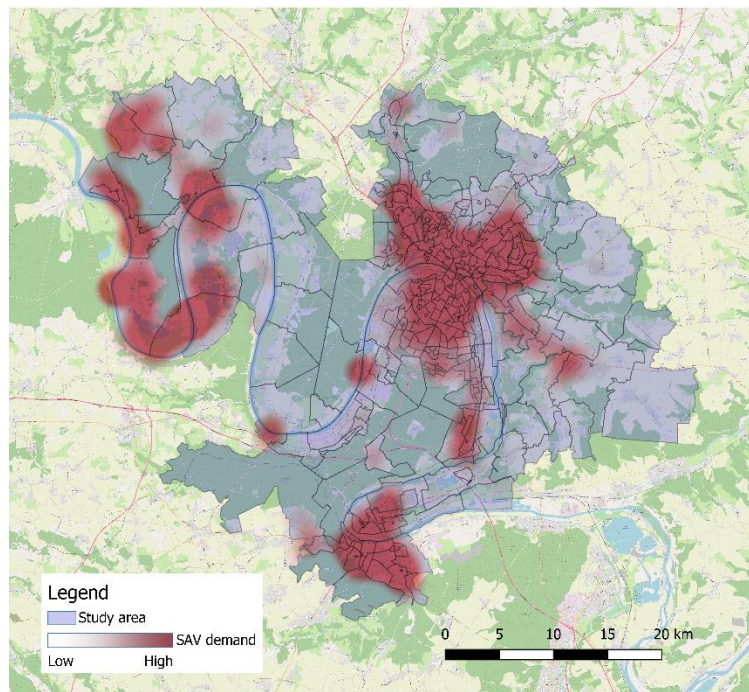
Table 5.2

Summary of SAV service metrics for the base-case scenario.

	SAV service with unlimited range
SAV modal share (%)	5.3
Average waiting time (min)	20.7
Average in-vehicle time (min)	46.0
Average detour time (min)	6.1
Fleet usage ratio (%)	50
Empty distance ratio (%)	15
In-vehicle PKT (km)	1.97 M
1 PAX ratio (%)	67
2 PAX ratio (%)	26
3 PAX ratio (%)	6
4 PAX ratio (%)	1
Average driven distance (km)	546
Max. driven distance (km)	866

5.4.2 Selection of charging station locations

To locate charging stations, the pick-up and drop-off points identified from the base-case scenario were used as the potential areas of the SAEV service requests. Fig. 5.1 shows a heat map of those point locations across the case study area. This figure shows that SAV users are picked up or dropped off in three main areas where agglomerations of population and facilities are located.

**Fig. 5.1.** The spatial distribution of SAV demand.

Since approximate locations for placing charging stations are needed, in both optimization processes, the SAV pick-up and drop-off points were spatially aggregated to the uniform cells. Each cell may contain only one charging station. As suggested by Asamer et al. (2016), since a complete tessellation

of the study area is required, hexagonal cells are used. Furthermore, this choice of geometric form allows us to consider equal distances between the centroids and the borders (while the charging stations are located in the centroid). The diameter of a hexagon cell is chosen to be 1 km. For P-Median optimization, the exact location of charging stations is assumed to be in the center of the hexagon. Fig. 5.2 shows selected hexagons (marked with triangles). This figure shows that charging stations are less scattered when MCLP optimization is employed. This occurs because by maximizing coverage location, the distances between demand hubs are somehow neglected. Therefore, the charging stations are rather located in the areas where there is a high number of pick-up and drop-off points. The P-Median optimization seeks, however, the potential locations of charging stations where the access distance from those hubs are minimum. As a result, the selected hexagons are not necessarily from where the potential demands are high.

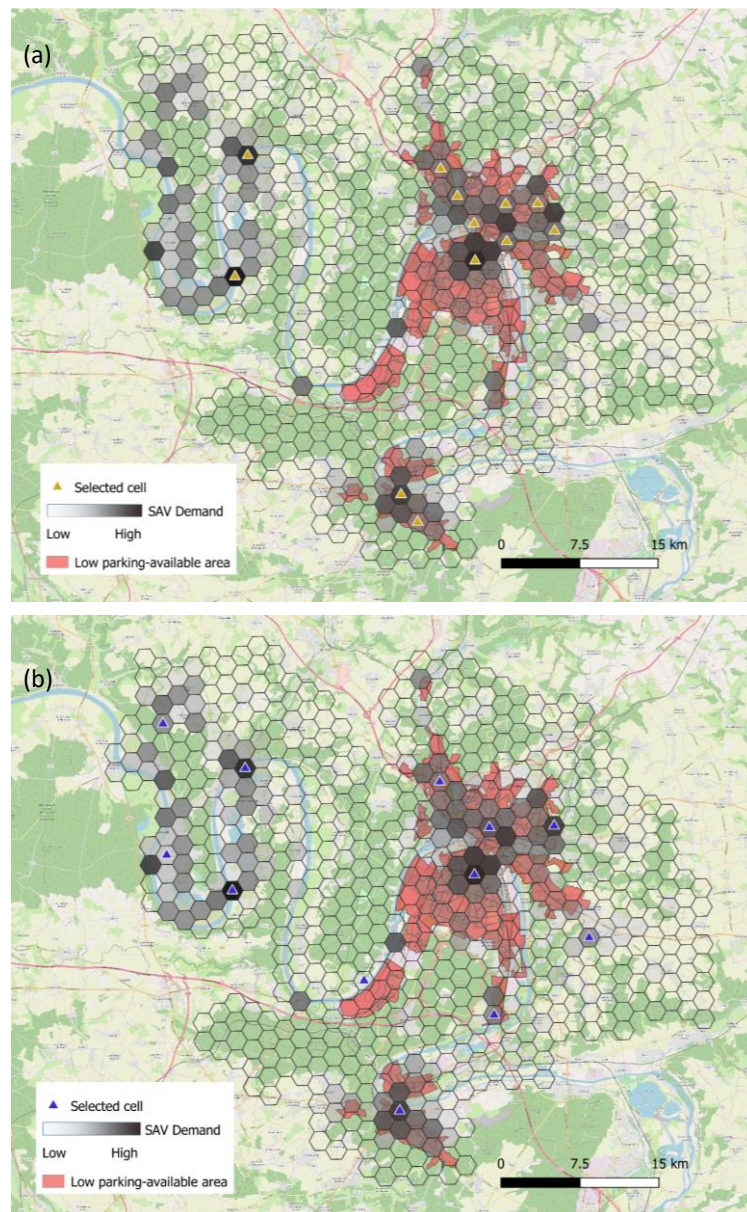


Fig. 5.2. Selected cells for locating charging stations employing different optimization approaches: (a) MCLP (b) P-Median.

The light red areas superposed in Fig. 5.2 show the zones where the parking places are limited. The population and trip attractions in those areas are particularly dense and land values are high. Therefore, in terms of capital expenditures, locating charging stations in areas with low parking availability may lead to excessive cost for the operator. In order to place charging stations outside of these areas, the P-Median optimization with an extra constraint is used. Fig. 5.3 shows the selected hexagons. As can clearly be seen, adding this constraint results in a different dispersion of charging stations specifically around the areas with low parking availability. These charging station locations are subsequently evaluated within the proposed framework of modeling and simulation simulations, and compared with the two prior strategies.

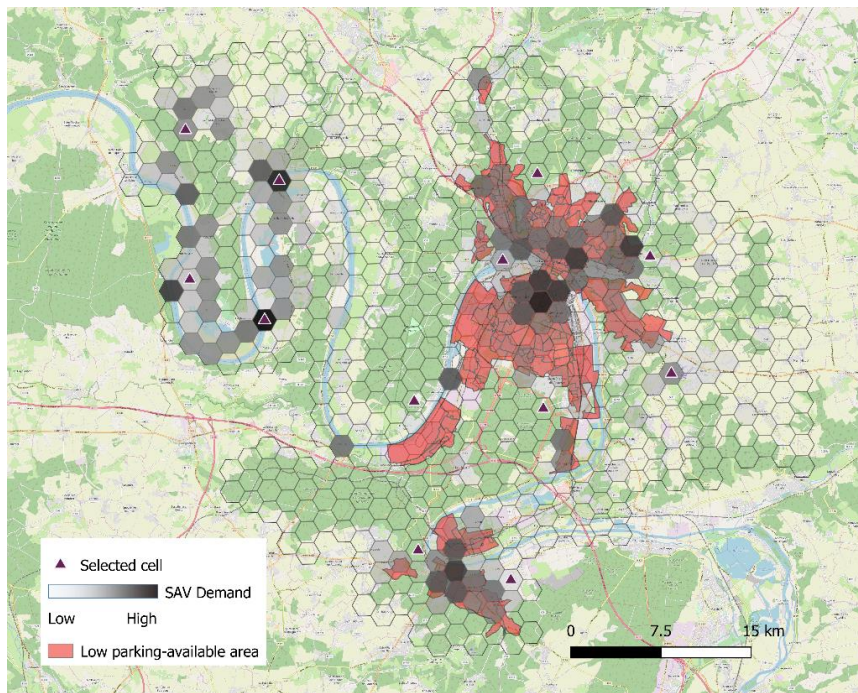


Fig. 5.3. Selected cells for locating charging stations outside the areas with low parking availability employing P-Median optimization.

5.4.3 Normal charging infrastructure

Based on the mentioned charging station placement strategies and two different SAEV battery capacities, six distinctive scenarios were simulated. These scenarios include combinations of medium-range and long-range SAEVs (41 and 50 kWh of battery capacity), and three charging station placement strategies; by maximizing coverage (MCLP) and minimizing distances between charging stations and potential demand hubs (P-Median), along with the P-Median strategy with avoiding placing the charging station in areas with low parking availability (P-Median with constraint). In all scenarios, each charging station is assumed to be equipped with 60 outlets of normal charging power (22 kW), which corresponds approximately to the ratio of 4.17 vehicles per EVSE outlet. This ratio is bigger than the one estimated by Chen et al. (2016) for SAEV with normal charge since the vehicle range in that study is shorter. The SAEVs with SoC of less than 20% are dispatched to the nearby charging stations after having dropped off a client (or clients). The SAEVs stay at charging stations until the battery is fully charged.

Table 5.3 shows the result highlighting the SAEV service performance metrics and user-related indicators. While simulations are performed for more than 24 hours due to the activity chains that exceed a day, metrics are only calculated for one day. Simulation results show that the SAEV modal shares vary from 3.8% to 4.3% for different charging station placements and battery capacities. These modal shares remain noticeably lower than that of non-electric SAV (5.3%, shown in Table 5.2). Because of the lower service availability due to going to charging stations and charging times along the day, the fleet usage ratio is decreased remarkably in all SAEV scenarios compared to the base-case scenario. The SAEVs perform extra VKT for going to the charging stations. Therefore, the empty distance ratios are increased compared to non-electric SAVs. The growth of empty distance ratios is maximal in the MCLP scenarios and minimal in P-Median scenarios with constraint. Similar to the fleet usage, the in-vehicle PKT decrease considerably and fluctuate significantly in different SAEV scenarios.

Table 5.3

Summary of SAEV service performance and user-related indicators.

Scenario	MCLP		P-Median		P-Median with constraint	
	Medium-Range	Long-Range	Medium-Range	Long-Range	Medium-Range	Long-Range
<i>SAEV</i>						
Battery capacity (kWh)	41	50	41	50	41	50
Modal share (%)	3.8	4.0	4.2	4.4	4.1	4.3
Fleet usage ratio (%)	31.5	34.5	36.5	38.7	35.6	41.3
Empty distance ratio (%)	21.7	19.9	19.6	18.6	19.1	18.7
In-vehicle PKT (km)	1.04 M	1.19 M	1.13 M	1.38 M	1.22 M	1.44 M
Average driven distance (km)	336	365	385	409	373	443
Max. driven distance (km)	660	682	650	698	735	667
<i>Charging station</i>						
Total plugged time (min)	381,300	399,700	433,800	451,150	443,300	496,500
Total queue time (min)	400,500	518,550	571,250	606,300	383,800	486,900
<i>User</i>						
Average waiting time (min)	13.5	13.4	13.3	13.9	13.3	13.2
Average in-vehicle time (min)	41.4	42.2	43.2	43.6	42.7	44.2
Average detour time (min)	4.7	4.9	5.0	4.8	4.9	5.3
1 PAX ratio (%)	72	72	67	67	70	70
2 PAX ratio (%)	24	24	28	28	25	25
3 PAX ratio (%)	3	3	4	4	4	4
4 PAX ratio (%)	<1	<1	<1	<1	<1	<1

The benefits for operators may be estimated based upon the in-vehicle PKTs and empty distances. By comparing scenarios considering these indicators, the P-Median strategy with the constraint of locating charging stations outside of areas with low parking availability remains the best performing strategy among all scenarios for both SAEV battery capacities. Within this strategy, the charging stations are more dispersed and particularly the demands for charging are more balanced across the stations during peak demand. This is also supported by the fact that the maximum coverage location (MCLP) was found to be a worse strategy in terms of service performance. In MCLP scenarios, the charging stations are rather located in the areas with high potential demand close to each other. This placement strategy limits the access of SAEVs, which are far from high potential demand areas, to a lower number

of stations and increases the access distance. This heterogeneity between charging station locations and potential demand hubs affect dramatically the in-vehicle PKT and fleet usage.

For all strategies, the long-range SAEVs outperforms other scenarios in terms of service performance indicators. The impact of battery capacity on service performance is discussed later in this section.

Since charging stations have a limited number of outlets, some SAEVs stand in line until charger outlets become available. This could potentially affect service performance. This metric is actually varying according to different strategies of charging station placement. To explore this variation, the total queueing and plugging times of SAEVs are estimated and compared. Table 5.3 shows that the total queue times are as significant as total plug-in times in all scenarios. The total queue time is slightly less than total plug-in time in only the P-Median strategy of charging station placement with a constraint. Given the total plug-in time and the number of outlets at each station (60 units), the results show that charger outlets are more efficiently used in the P-Median strategy of charging station placement. However, the total queue time remains significant and needs to be improved. For this purpose, two main scenarios are simulated : (i) the charging stations equipped with rapid chargers and (ii) the charging stations equipped with higher number of chargers. The obtained results will be discussed later in this section.

The user-related indicators do not significantly change amongst all scenarios of charging station placement. The average waiting time varies between 13.2 and 13.9 minutes. Compared to the non-electric SAV, this indicator decreased meaningfully. This decrease is due to the lower SAEV service demand. In fact, since the service is partially not available, a lower level of services compared to other alternatives is provided. Thus, the requests for SAEVs decrease. In all SAEV scenarios, the average detour time fluctuates slightly around 5 minutes. Considering PAX ratios of those scenarios, a correlation is observed between charging station placement and vehicle occupancies. This may occur when there is no strategy of rebalancing. The SAEVs that need to be charged are dispatched to the areas where the spatial trip patterns of travelers are different. In fact, once an SAEV is fully charged, it stays outside the charging station until a request (or some requests) is upcoming. The ride may be shared according to the trip patterns of on-board traveler(s) and next upcoming requests in those areas. As a result, PAX ratios remain almost unchanged for both vehicle ranges for the same charging station locations but vary between scenarios.

5.4.4 Rapid charging infrastructure

As mentioned before, significant total queue times observed in all SAEV scenarios may strongly affect the performance of services. A solution for reducing those times can be to equip the charging stations with rapid charger outlets (or level 3 chargers). This EV supply equipment is more expensive for the operators but could be compensated or even neglected by having greater in-vehicle PKT. In order to explore the impacts of deploying rapid charging infrastructure, the same scenarios are simulated with the charging stations equipped with 43 kW outlets (instead of 22 kW). Table 5.4 shows the changes in service performance metrics and charging plug-in and queue times. As shown in this table, empty distance ratios increased in all scenarios with the maximum values for charging stations located according to the maximized coverage. This again indicates that one of the reasons for the ineffectiveness of this placement strategy is unbalanced dispersion of charging stations along the service area. Thus, SAEVs that are in “go-to-charge” mode but are far from available charging outlets have to wait for

charging and, consequently, are not efficiently used. Nevertheless, by introducing rapid charging infrastructure, the nearest outlet to each SAEVs becomes available in a faster time.

The empty distance ratios increase in all scenarios except for the constraint-free P-Median strategy. In the P-Median strategy, significant improvements in all service performance metrics are observed. Considering in-vehicle PKT and empty distance ratio indicators, it is demonstrated that both P-Median strategies perform almost similarly and remain much better than the strategy of maximizing coverage of potential demand. The important improvements on SAEV service metrics of P-Median strategy occurred as the introduction of rapid chargers allowed to decrease excessive queue times for the charging outlets located at potential demand hubs. By providing rapid charging infrastructure in those areas, SAEVs become more available at a closer distance to the high demand hubs. As a result, VKTs and in-vehicle PKTs improve. The empty distance ratios of constraint-free P-Median strategy are slightly lower compared to the one with constraint, suggesting that the charging stations are accessible within relatively lower distances.

Table 5.4

Summary of SAEV service performance indicators and the changes after deploying rapid charging infrastructures.

Scenario	MCLP		P-Median		P-Median with constraint	
	Medium-Range	Long-Range	Medium-Range	Long-Range	Medium-Range	Long-Range
<i>SAEV</i>						
Fleet usage ratio (%)	37.5	41.2	41.4	42.7	41.6	42.3
(relative change)	(+19%)	(+19%)	(+13%)	(+10%)	(+14%)	(+2%)
Empty distance ratio (%)	22.8	22.7	19.2	18.3	21.1	18.8
(relative change)	(+5%)	(+14%)	(-2%)	(-2%)	(+10%)	(+1%)
In-vehicle PKT (km)	1.24 M	1.39 M	1.43 M	1.56 M	1.42 M	1.56 M
(relative change)	(+19%)	(+17%)	(+27%)	(+13%)	(+16%)	(+8%)
<i>Charging station</i>						
Total plugged time (min)	212,950	226,400	229,700	240,250	245,050	242,700
(relative change)	(-44%)	(-43%)	(-47%)	(-47%)	(-45%)	(-51%)
Total queue time (min)	92,100	143,650	203,950	122,650	19,700	79,150
(relative change)	(-77%)	(-72%)	(-64%)	(-80%)	(-95%)	(-84%)

5.4.5 Variation of EVSE outlet units

Table 5.4 shows that despite major improvements on service performance indicators in constraint-free P-Median strategy, the total queue times remain significantly high and are the highest among all scenarios, indicating the necessity of having more charging outlets in each station (lower number of vehicles per EVSE outlet). To explore the impact of the vehicle per EVSE outlet variation on SAEV service performance, different capacities of charging stations for both P-Median strategies are simulated. In these scenarios, only normal charging speed (22 kW) is considered. Fig. 5.4 shows the changes and compares them. As expected, by increasing the number of outlets per charging station, the total charging queue times decrease in all scenarios. The reason for this is that more outlets are available and thus fewer SAEVs pass the time in queue. The in-vehicle PKTs, however, fluctuates around a maximum value. Considering long-range SAEVs, in both strategies of charging station placement, the maximum in-vehicle PKT value is reached when 90 outlets per station (vehicle/EVSE outlet ratio: 2.78) are

provided. Therefore, it is seen that in the case when SAEVs are not rebalanced, having more charging space and less total charging queue time does not necessarily result in higher service performance, particularly in terms of revenue. The explanation for this issue is that by providing more outlet units per station, SAEVs are dispatched rather to the nearest charging stations, because in this case, the probability of having an available outlet in the nearest charging station is high. Those charging stations are located in limited areas and are situated near each other, particularly in the case of P-Median strategy of charging station placement. As a result, SAEVs are somehow rebalanced and dispatched less dispersedly and, consequently, are accessible with a lower level of services. Thus, the service performance indicators and especially in-vehicle PKT decline slightly. It is important to underline that by enabling rebalancing different results may be obtained.

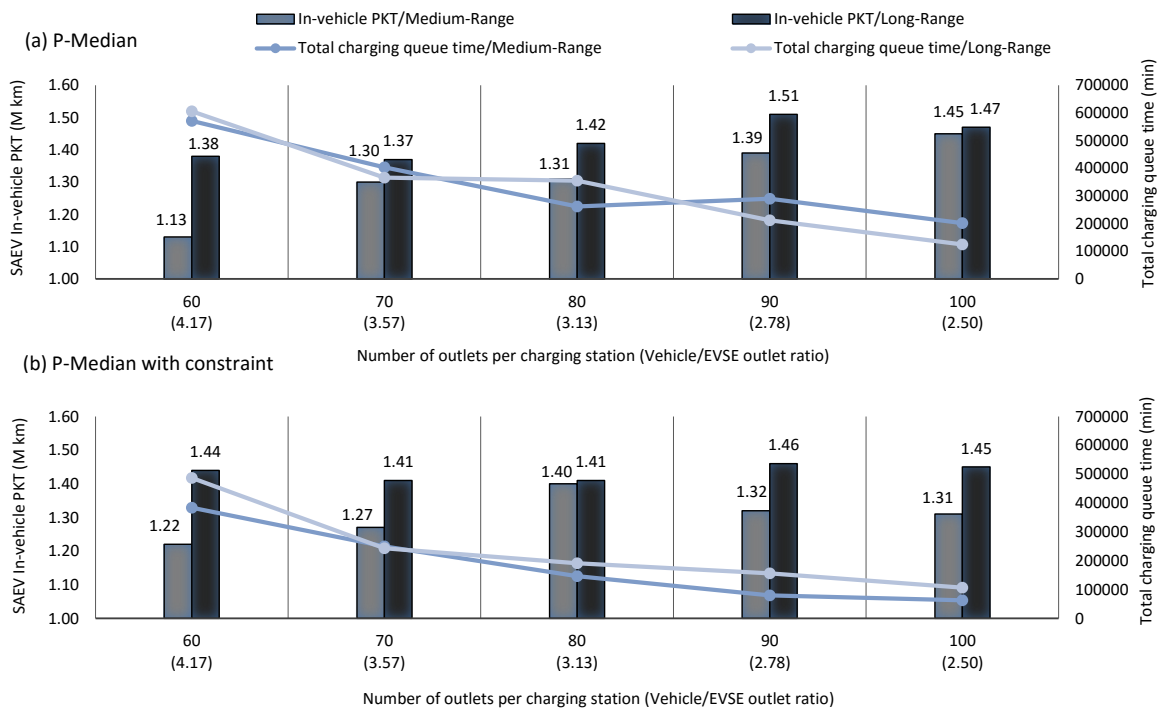


Fig. 5.4. Changes on SAEV service performance indicators according to the different number of outlets per charging station for medium-, and long-range vehicles and two scenarios of charging station placement: (a) P-Median; (b) P-Median with constraint.

Fig. 5.5 presents the charging station occupancy rates (the number of SAEVs charged in each charging station during the given day) for both P-Median strategies and vehicle ranges. The light bar with dashed line corresponds to the scenario with the best-performing number of outlet units. The dark bar corresponds to the scenario with the maximum number of outlets (100 units), except for medium-range SAEVs of P-Median strategy, where the best number of output units is the maximum one. For this scenario, the occupancy rate is compared with that of lower capacity. Fig. 5.5 shows that demands for charging are more spatially dispersed in the case of the best-performing number of charging outlet units for long-range SAEVs (particularly there is less demand for the most occupied charging station). By comparing both strategies of charging station placement, it can be also seen that locating charging stations in areas with low parking availability results in excessive usage of some charging stations (e.g., charging station number 6 in P-Median without constraint).

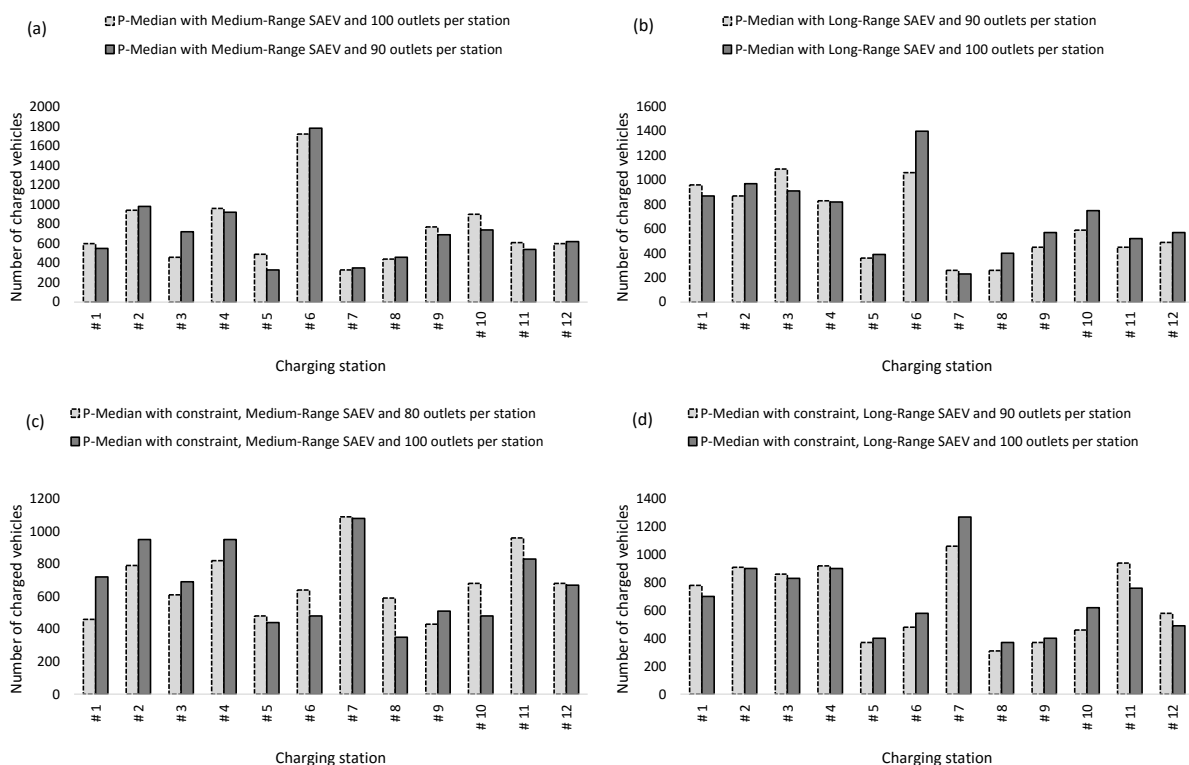


Fig. 5.5. The occupancy rates of charging stations (the number of charged SAEVs per charging station during a given day) estimated for the best and maximum numbers of outlets (lower charging outlet units if the best number of units is the maximum one).

For medium-range SAEVs, the greatest in-vehicle PKT is reached when 100 outlet units in P-Median strategy are assumed. In this case, compared to the lower charging spaces in the stations (90 outlet units per station), for the nearly similar dispersity of demands for charging (Fig. 5.5), a lower charging queue time occurs, leading to the increased in-vehicle PKT. This in-vehicle PKT, however, is the highest when 80 outlet units in P-Median strategy with a constraint of avoiding locating them in areas with low parking availability are considered. Here, the limitation of charging station space to 80 units of charging outlets results in a better allocation of SAEVs to the areas where different trip patterns of users lead to a higher in-vehicle PKT. Table 5.5 presents this phenomenon. As can be seen, while the average trip distances of SAEV users in other scenarios are nearly similar for both numbers of outlets per station, this distance declines considerably when a larger capacity of charging station is assumed for the scenario in question. The explanation for this result is that in the P-Median strategy of charging station placement with constraint, charging stations are located on the sidelines of areas with high potential demand. Accordingly, with lower charging outlet units per station, SAEVs that need charging are dispatched to a wider set of available charging stations, which are consequently farther from nearest demand hubs. The trips performed by the travelers coming or going to the sideline of areas with high potential demand are longer. Hence, while providing service to those travelers without extending total charging queue time during the day, total in-vehicle PKT increases.

Table 5.5

SAEV user average trip distances for different scenario.

Scenario	P-Median		P-Median with constraint					
	Medium-Range	Long-Range	Medium-Range	Long-Range	Medium-Range	Long-Range		
Number of outlets per station	90	100	90	100	80	100	90	100
SAEV user average trip distance (km)	32.5	32.6	35.6	35.6	33.6	32.9	33.6	33.4

5.4.6 P-Median strategy with mixed stations

As stated before, locating spacious charging stations in high-density areas may be very expensive for the service provider. In P-Median strategy of charging station placement, two stations are located in the city center. In the new scenario, the number of outlet units in those stations are reduced and the capacity of charging stations that are located around the city center are increased (see Fig. 5.6; the charging station with 10 EVSE outlet units is situated in Rouen Old Town). The overall vehicle/EVSE outlet ratio is supposed to be 2.78, so that the results with those of previous scenarios can be compared. The simulations are done assuming rapid charging in the stations localized in the city center and normal charging in other stations.

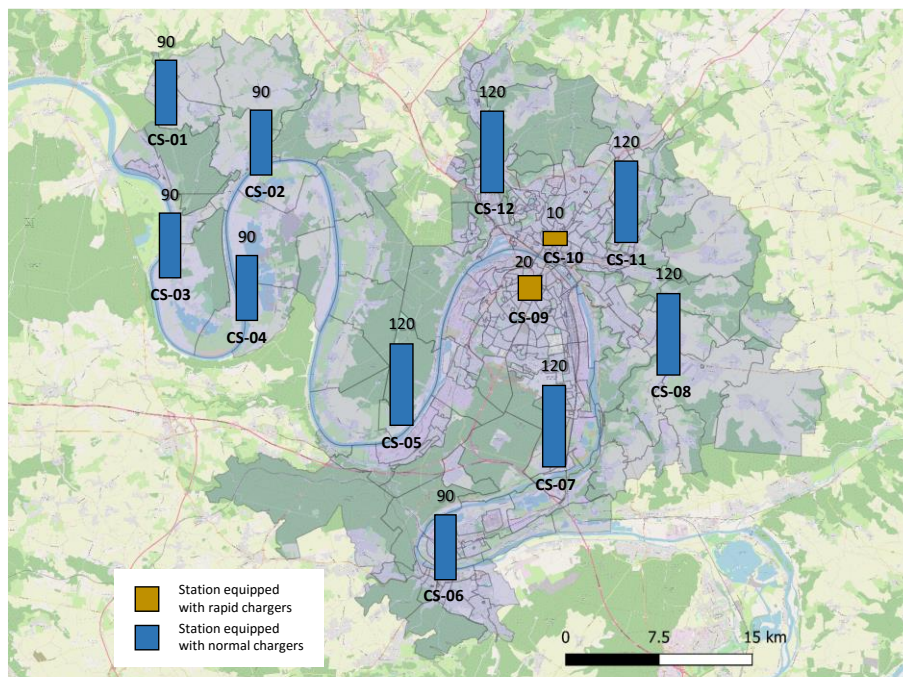
**Fig. 5.6.** Distribution of charging station outlet units in mixed station scenario.

Table 5.6 illustrates the results. As seen here, contrary to what was expected, the in-vehicle PKT for both vehicle ranges (battery capacities) decreases. However, the empty distance ratios improve. This occurs since the SAEVs being in the northern regions of the city center area and are in “go-to-charge” mode have not enough battery to access charging stations located in southern regions. Thus, they wait for the rapid charging stations, in which the number of EVSE outlets are limited, or they try to reach the normal charging stations situated in northern regions, which have already important demands.

Consequently, despite the total plugged time that is improved due to the rapid charging, the total queue time increases significantly and those vehicles become less available. In order to avoid high queue time in mixed stations scenario, the limited SoC for going to charge has to be increased or more EVSE outlets in stations located in the city center or northern area should be provided.

Table 5.6

Comparison of SAEV service performance indicators for both P-Median strategies of similar and mixed stations.

Scenario	P-Median		P-Median with mixed stations	
	Medium-Range	Long-Range	Medium-Range	Long-Range
<i>SAEV</i>				
Empty distance ratio (%)	19.7	19.7	19.3	18.9
In-vehicle PKT (km)	1.39 M	1.51 M	1.27 M	1.39 M
<i>Charging station</i>				
Total plugged time (min)	500,050	538,150	410,950	445,700
Total queue time (min)	289,750	212,400	446,750	391,700

5.4.7 SAEV battery capacity (vehicle range)

The previously described simulations incorporate two different battery capacities for each strategy of charging station placement. In all scenarios, the long-range SAEV outperforms medium-range ones in terms of in-vehicle PKTs and empty distance ratios. Fig. 5.7 shows the SAV hourly in-service rate in the base-case scenario illustrating the temporal distribution of potential SAEV demands. This figure shows also the SAEV hourly total plug-in times of the mentioned best-performing scenarios (i.e., best vehicle/EVSE outlet ratio) using normal charge infrastructures. As can be seen from Fig. 5.7, according to the hourly usage pattern of SAV service, there are two peak hours in a day: morning (8-10 a.m.) and evening (4-8 p.m.). Meanwhile, in all scenarios of SAEV, the peak of charging times occurs after the morning peak hour. In fact, those battery capacities (and accordingly vehicle ranges) are almost enough to meet the demand of morning peak hour. After this time, the majority of medium-range SAEVs face rapidly limited SoC (20%) and are therefore dispatched to the nearby charging stations. In this case, the SAEVs are rather plugged in during the off-peak hours and are ready for service in the evening peak hour. In the case of long-range SAEVs, as mostly SAEVs SoC are enough to meet the demands of midday off-peak hours, they continue to do the service and go to the charging stations later in a day. Hence, important plug-in times are rather in the evening peak hour. This actually leads to a lower service performance since a substantial part of SAEVs are not available during evening demand peak hour. Therefore, considering the best-performing scenarios of charging outlet units, the difference of in-vehicle PKTs for both SAEV battery capacities are not as significant as expected (Fig. 5.4). This actually indicates the importance of battery capacity (vehicle range) and its impact on service performance. Lower SAEV battery capacity may result in missing morning demand. Moreover, a higher SAEV battery capacity without any change on limited SoC cannot be necessarily beneficial because the operator is obliged to send the SAEVs to the charging stations during midday off-peak hours due to unmatched demand temporal pattern and service availability. Nevertheless, increasing limited SoC (by more than 20%) in long-range SAEV may lead to having more charging station alternatives when a

vehicle is in “go-to-charge” mode as well as avoiding peak charging times in evening peak demand times.

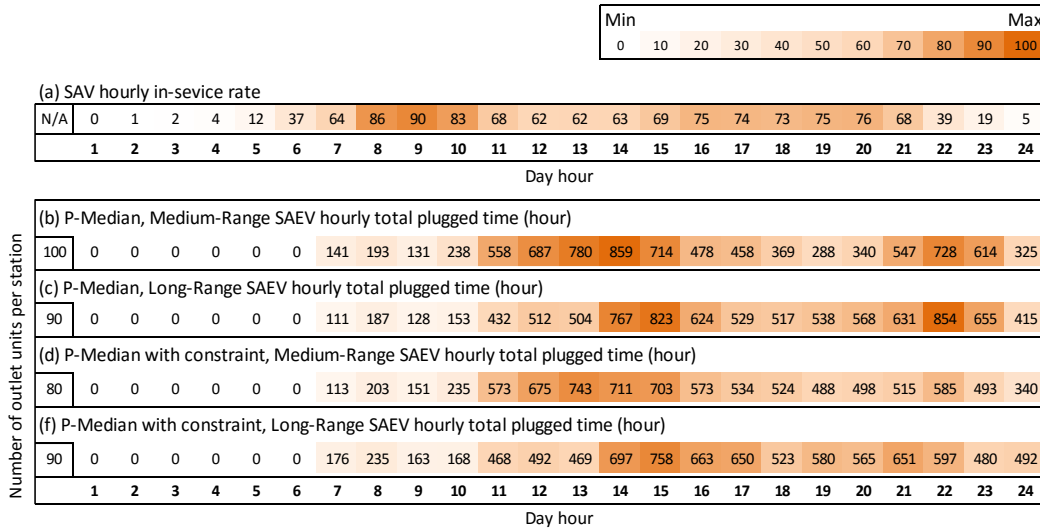


Fig. 5.7. The comparison of SAV hourly in-service rate (base-case scenario) and SAEV hourly total plug-in times.

5.4.8 SAEV battery swapping

Fig. 5.4 shows that by providing more charging space, the P-Median strategy of charging station placement becomes more efficient in terms of in-vehicle PKT. However, its total charging queue time remains relatively high and still significant. By decreasing this time, the SAEV service will be more available and thus a greater in-vehicle PKT can be achieved. A potentially cost-effective solution, particularly for the stations located in the areas with high potential demand, is to provide battery swapping infrastructures (Adegbohun et al., 2019; Zhang et al., 2018). At battery swapping stations (BSSs), depleted batteries can be exchanged with the recharged ones. Since the process is faster than charging, this will guarantee the availability of SAEVs by reducing charging and queue times. Furthermore, less space would be needed.

To explore the impacts of battery swapping on SAEV service performance, the same scenarios with BSSs located according to both P-Median strategies were simulated. It is assumed that in each BSS, batteries for 20 SAEVs can be swapped at the same time and the swapping process takes 5 minutes. Table 5.7 presents obtained results. As can be seen, the in-vehicle PKT increases significantly in all scenarios. This indicator remains obviously lower than that of non-electric SAV (1.97 M). Similar to the previous scenarios of SAEV, the empty distance ratios fluctuate around 20% and are bigger than the empty distance ratio of non-electric SAV (15%). This result is attributed to the empty drive for going to the BSS during the day and returning to the initial depots at the end of the day after being fully charged. Even if the battery swapping process takes little time, due to the limited number of BSS spaces and high demand in some areas, the total queue time does not reach zero. The total queue times are however insignificant for all scenarios; i.e., roughly less than 1 minute per SAEV. Considering in-vehicle PKT and empty distance ratio as the main indicators of service performance, it seems that a service of long-range SAEVs with the P-Median strategy of BSS placement outside of the areas with low parking availability is the best-performing scenario. This conclusion is contrary to what has been observed

previously by increasing charging spaces, where the P-Median strategy with the best number of outlets and without any constraint showed a slightly higher in-vehicle PKT. Furthermore, when the medium-range SAEVs are simulated with the BSS infrastructures, the in-vehicle PKT of the P-Median scenario outperforms the other scenarios. This is actually due to two main reasons. First, since there is no strategy of rebalancing in those scenarios, the location of BSSs somehow affects the results by distributing SAEVs dissimilarly during the day. As stated before, in the P-Median strategy of charging or battery swapping station placement, those stations are centralized to the areas with high potential demand near each other. Accordingly, when SAEVs are dispatched to the BSSs, they are implicitly rebalanced less dispersedly. Consequently, SAEVs become less attractive in terms of access time and consequently the demand decreases (50 410 rides compared to 51 580). This is not, however, the case of medium-range SAEVs, when the in-vehicle PKT of P-Median strategy is higher. In fact, by deploying BSS infrastructure, SAEVs are traveled with longer distance compared to the previous scenarios (i.e., rapid charging and more charging space), especially in morning peak hour. Therefore, they reach rapidly critical SoC and, consequently, SAEVs are dispatched rather during morning peak hour to the nearby BSSs. In the P-Median strategy of BSS placement outside of areas with low parking availability, BSSs are accessible with longer distances. This result can be observed by comparing empty distance ratios. Thus, the service becomes less available during peak hours, which results in lower in-vehicle PKT. This result again underlines the importance of battery capacity (vehicle range) and its impacts on SAEV service performance.

Table 5.7

Performance indicators of SAEV service with BSS infrastructure.

Scenario	P-Median		P-Median with constraint	
	Medium-Range	Long-Range	Medium-Range	Long-Range
<i>SAEV</i>				
Fleet usage ratio (%)	49.9	50.9	50.1	53.0
Empty distance ratio (%)	20.9	19.6	21.5	19.8
In-vehicle PKT (km)	1.77 M	1.82 M	1.73 M	1.88 M
Total VKT (km)	1.62 M	1.64 M	1.61 M	1.69 M
<i>BSS</i>				
Total queue time (min)	2,700	3,050	1,050	1,060
Extra battery (unit)	2,050	2,260	1,960	2,350

Extra battery units required to supply swapping needs are estimated for each scenario. It is assumed that BSSs are equipped with adequate normal chargers (22 kW) and extra batteries are plugged in immediately after being detached from SAEV. The charging time depends on the remaining SoC. For a fully discharged battery, it takes 112/136 minutes to completely recharge (depending on the battery capacity, i.e., 41/50 kWh). Once a battery is fully charged, it can be used for the next upcoming request at the same BSS. Table 5.7 shows that the numbers of required extra battery units in all scenarios are less than fleet size (3,000 SAEVs). This ratio varies between 56% and 78%. This actually occurs since batteries are recharged at a lower time than intervals of two battery swapping for each SAEV. Therefore, a battery can be reused for multiple vehicles during a day. Extra battery units needed for the same vehicle ranges in both strategies of BSS placement are almost similar. This result suggests the correlation

between battery capacities and the number of extra batteries. Clearly, the number of extra batteries varies slightly for each vehicle range according to the total VKT.

It is important to mention that the additional batteries represent an additional cost for the operator. Hence, a financial analysis is required to compare scenarios considering service profits. However, due to the high uncertainty of future SAEV service and infrastructure costs, this thesis evaluates and analyses only transport-related indicators.

5.5 Conclusion

This chapter aimed to investigate the impact of charging infrastructure configurations and vehicle's battery capacity on service performance. For this purpose, the proposed framework of modeling and simulation, presented in Chapter 2, was employed. To locate charging and battery swapping stations, three placement strategies were generated in a separate model. These strategies were based on two optimization models: (i) maximizing coverage and (ii) minimizing the distance between potential demands and stations. Simulations of non-electric SAVs and SAEVs with two different battery capacities across the Rouen Normandie provide initial insights. As suggested by these simulations, assuming a fleet of SAEVs, given the relatively lower range of today's electric vehicles, it will be necessary to recharge the majority of vehicles during the day. By providing one normal charger per approximately four SAEVs, and limiting vehicle range according to the battery capacities of an autonomous EV used for the experimentation (Renault Zoe, 41 and 50 kWh), our simulations show that the performance indicators become dramatically worse in all scenarios compared to a non-electric SAV service. Particularly, a significant reduction of in-vehicle PKT, which is an indicator of direct revenue for operators, and important growth on empty VKT are observed. After replacing normal chargers with rapid chargers (43 kW, instead of 22 kW), important improvements are observed. By increasing the number of outlets of normal chargers up to 33-67%, SAEVs service reaches the best performance level. Nevertheless, it is found that these improvements result in almost similar in-vehicle PKT compared to the case when the rapid charging infrastructure was outspread. This result raises the question of whether deploying rapid charging stations is financially more beneficial than providing more charging space. This chapter also highlighted that by providing a much lower capacity of battery swapping in each station and unlimited normal charge outlets, up to 88-95% of initial in-vehicle PKT (estimated for unlimited-range SAV) may be achieved. Given the service performance indicators of battery swapping simulations, one can conclude that this charging infrastructure is the best alternative among all scenarios.

Importantly, the choice of charging and battery swapping station placement strategy is found to have a profound effect on service performance indicators. In general, locating charging infrastructure by minimizing distances between potential demands and charging stations leads to much better in-vehicle PKT than when employing the coverage maximization. It is also observed that the centralization and lower dispersity of charging stations in the low number of charging outlets per SAEVs (approximately one unit per four vehicles) may decline service performance indicators. Further analysis shows that when battery swapping infrastructure is provided, the P-Median strategy of BSS placement is the best strategy. The results also reveal that the battery capacity of SAEVs has to be set according to the traveled

distances of morning peak hour and limited SoC for sending vehicles to charging stations so that the maximum charging times occur during midday off-peak hours.

Chapter 6

Conclusion

This thesis has the objective to support the design of SAV and SAEV services considering dynamic-demand, responsive to the traffic, in a multimodal network with user taste variation integrated into the model. An activity-based multi-agent simulation framework and a set of related key metrics were proposed and employed to evaluate the performance of services and measure the impacts on the network and users' behavior. Simulation experiments were conducted based on the real data of the transportation system of the Rouen-Normandie metropolitan area (France) and the specifications of an autonomous vehicle, used for ongoing experimentation in the region of Rouen.

6.1 Contributions

A review of the existing literature (Chapter 2) reveals a large attention given today to modeling and simulation of SAVs. However, most of the reviewed investigations neglect the dynamic interaction of service and demand. Particularly, demand is often considered static or based on market penetrations, or simulations incorporate only one mode with no mode choice decision and/or no congested network. In real-life transportation networks, any changes to the transport supply, including the configuration of new shared services, can result in completely different service demands. Consequently, traveler behavior, congestion, the environment, and urban form are affected in short, mid, and long terms. This indicates the importance of considering the balanced tradeoff between demand and proposed services. Especially, when designing and planning the future SAV services, the dynamic demand that responds to the congested network in a multimodal context can significantly affect the configuration of appropriate services. Chapter 2 addresses this issue and proposes a framework of comprehensive modeling and simulation.

Despite the advantages of activity/tour-based multi-agent approaches, particularly in terms of granularity of data and outputs, most of the reviewed simulations relying on this approach are based on a homogeneous structure of behavior. This implies that all travelers have similar preferences when they make SAV choice decisions. This similarity can certainly affect the service design, especially considering that traveler-related attributes are significant in AV mode choice decision (Chapter 2). This research gap was addressed in Chapter 3 by integrating user taste variation into the multi-agent simulation and assessing its impacts on SAV service configuration and particularly fleet sizing.

The design of an SAV service employing comprehensive modeling and simulation, and using proper key performance metrics, considering major aspects of service configuration and vehicle specifications, is one of the missing components that found in the literature. To address this issue, Chapter 4 provides an investigation of SAV service performance evaluation, considering the strategy of individual or shared rides, vehicle rebalancing, service price, vehicle capacity, and fleet size.

Assuming a fleet of electric SAVs (SAEVs), it is found from the literature review that the related charging infrastructure and vehicle range have attracted less attention, in particular when such a service is simulated employing more sophisticated demand modeling and especially dynamic-demand approaches. Chapter 5 addressed this research gap and assessed the impacts of SAEV vehicle specification (i.e., battery capacity or vehicle range), and the configuration of required infrastructure including the charging station placement, charging speeds, and available spaces in charging stations on service performance.

6.2 Key findings and insights

In the following, the key findings of this thesis and answers to the research questions are described:

- Activity/tour-based travel demand modeling coupled with multi-agent simulation can provide required data with enough granularity to design SAV service and to assess its impacts in a multimodal network. Such an approach requires essentially very fine-grained data as input, particularly synthetic population and activities or trip-chains of each individual.
- Integrating survey data into the model shows the significant importance of traveler's trust and willingness to use varying the SAV service use and the required fleet size in both non-ridesharing and ridesharing concepts assuming distance-based or fixed monthly cost rates. The obtained results underline the effect that different SAV users with different trip patterns and taste variation may have on the service usage and prove the importance of considering that user differentiations in SAV service demand modeling and simulation.
- The performance of SAVs is strongly correlated with the service configuration, particularly the fleet size and the strategy of the ride (i.e., non-ridesharing or ridesharing). Similarly, enabling vehicle rebalancing may have a profound effect on service performance. Regarding vehicle characteristics, obtained results from vehicle capacity variation show that the benefits of more than 4 seats in SAVs are limited.
- Given the average driven distances of non-electric SAVs obtained from optimum scenarios for the case study area and the relatively lower traveling range of today's electric vehicles, the results indicate that future SAEVs with today's range will necessarily need charging during the service time along the day.
- Assuming one normal or rapid charger per approximately four SAEVs, and limiting vehicle range according to the battery capacities of an autonomous EV used for ongoing experimentation, the simulations show that the service performance indicators are becoming dramatically worse compared to non-electric SAV service. Particularly, a significant reduction of in-vehicle PKT, which is an indicator of direct revenue for the operator, and a considerable growth of empty VKT are observed. Furthermore, it is found that an increase in the number of charger units and deployment of rapid charging result in a similar performance. According to the obtained results, it is suggested setting the battery capacity according to the demand of morning peak hour.
- The choice of charging and battery swapping station placement strategy is found to have a profound effect on service performance indicators. The centralization and lower dispersity of charging stations in the limited number of charging outlets per SAEVs may result in the decline of service performance indicators.
- Apart from increasing vehicle range and using bigger batteries, battery swapping has a great impact on SAEV service effectiveness and efficiency and may represent a good solution to reduce unused times of charging and queuing for the charge.

Further results and analyses emphasize the importance of simultaneous incorporation of dynamic demand, user taste variation, mode choice mechanism (in a multimodal context), and dynamic representation of traffic and congested network in the design, modeling, and simulation of non-electric and electric SAV systems.

6.3 Limitations

The investigations conducted within this thesis are limited to a certain degree. The first limitation is related to data, which is inherent to the SP survey in general. At the time of writing this thesis, commercial fleets of SAVs were not yet on the road and thus there were no RP data at hand. As a result, an issue-specific SP survey was needed. Such surveys might not reflect accurately the real behavior of travelers with regard to using a driverless car. While this thesis shows the importance of considering traveler-related attributes on SAV service performance and design, further studies and particularly those that focus on the planning of commercial SAV services should consider a more relevant data such as data obtained from local experimentations.

The next limitation is related to the mode choice mechanism employed in this work. Due to the lack of data, the VoT in the estimation of LoS and disutility equations was considered similar for all travelers and trip purposes. Even if the assumed VoT for SAV users are different in the simulation due to a coefficient that varies according to the household income level, future work should consider a varied VoT and develop mixed logit model in order to differentiate this value for all modes in the simulation.

Computational time is also an important issue in multi-agent simulation. Due to this constraint, only door-to-door SAV services are investigated in this thesis. Hence, the potential of this service for the last-mile of journeys, performed using public transport is neglected. In fact, by considering the inter-modal network of public transport and SAVs, a significant number of decision alternatives at the individual level are possible. Handling and evaluating such a huge set of decisions in a congested city-scale network are computationally intensive and time-consuming. Such an issue is unfortunately general to multi-agent simulation. Although few studies employing activity/tour-based multi-agent simulation incorporate last-mile problem, however, due to the high computational time, the population in those studies is downscaled at a very low rate.

This thesis is also limited by a short-term planning of SAV services. Although the term “activity-based” is used to emphasize the integration of all trip-chains and the possibility of modifying activity end times in MATSim, this term, from the transportation planning point of view, does not reflect the use of a real activity-based approach since the destination choice decisions are not enabled in the simulation. Given expected impacts of SAVs in mid-term and long-term, especially on land occupation, it is mandatory to integrate land-use into activity/tour-based multi-agent transport models in the future investigations.

Finally, due to the specific calibration of the model, the lack of destination choice, and the obligation of simulating only door to door services, trips with long distances are captured by SAVs in the simulations presented in Chapter 4. Even if these limitations do not affect the results of the impact assessments on SAV service configuration, future works should consider all that limitations to successfully design the service in a real-life context.

6.4 Perspectives

While conducted investigations and results obtained within this thesis offer a broad and new understanding of service performance and design of non-electric and electric SAVs, there remain several investigating opportunities. For example, rather than having the same pricing scheme for all rides, future efforts should examine dynamic pricing (e.g., time-based or demand-based) and evaluate its impacts on

service demand and configuration. In addition, different rebalancing strategies may be proposed and evaluated within the employed framework of modeling, simulation, and design. Regarding charging infrastructure of SAEVs, several other aspects are open to investigation in future works. Instead of having the same number of charging spaces or the same charging speed in all stations, future efforts could examine potential combinations of normal and rapid charging as well as different numbers of chargers in the stations. The proposed framework of modeling, simulation, and service design can also be extended to integrate and evaluate different dispatching strategies for the allocation of accessible charging stations and outlets to SAEVs as well as for the consideration of pre-emptive charging. Understanding the financial tradeoff between service benefits (coming from passenger kilometer traveled) and costs (coming from e.g., empty VKT, and charging infrastructure configuration) is another important prerequisite for delivering SAV and SAEV services, which is suggested to be investigated in future works.

Bibliography

- Adegbohun, F., von Jouanne, A., Lee, K., 2019. Autonomous Battery Swapping System and Methodologies of Electric Vehicles. *Energies* 12, 667. <https://doi.org/10.3390/en12040667>
- Adnan, M., Pereira, F.C., Lima Azevedo, C.M., Basak, K., Lovric, M., Raveau, S., Zhu, Y., Ferreira, J., Zegras, C., Ben-Akiva, M., 2016. SimMobility: a multiscale integrated agent-based simulation platform.
- Agatz, N.A.H., Erera, A.L., Savelsbergh, M.W.P., Wang, X., 2011. Dynamic ride-sharing: A simulation study in metro Atlanta. *Transp. Res. Part B Methodol.* 45, 1450–1464. <https://doi.org/10.1016/J.TRB.2011.05.017>
- Al-Maghraoui, O. Al, Vosooghi, R., Mourad, A., Kamel, J., Puchinger, J., Vallet, F., Yannou, B., 2019. Shared Autonomous Vehicle Services and User Taste Variations: Survey and Model Applications.
- Al-Maghraoui, O., 2019. Designing for Urban Mobility - Modeling the traveler experience. *Interfaces*, Université Paris Saclay.
- Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., Rus, D., 2017. On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. *Proc. Natl. Acad. Sci.* 114, 462–467. <https://doi.org/10.1073/pnas.1611675114>
- Asamer, J., Reinthaler, M., Ruthmair, M., Straub, M., Puchinger, J., 2016. Optimizing charging station locations for urban taxi providers. *Transp. Res. Part A Policy Pract.* 85, 233–246. <https://doi.org/10.1016/J.TRA.2016.01.014>
- Auld, J., Hope, M., Ley, H., Sokolov, V., Xu, B., Zhang, K., 2016. POLARIS: Agent-based modeling framework development and implementation for integrated travel demand and network and operations simulations. *Transp. Res. Part C Emerg. Technol.* 64, 101–116. <https://doi.org/10.1016/J.TRC.2015.07.017>
- Azevedo, C.L., Marczuk, K., Raveau, S., Soh, H., Adnan, M., Basak, K., Loganathan, H., Deshmunkh, N., Lee, D.-H., Frazzoli, E., Ben-Akiva, M., 2016. Microsimulation of Demand and Supply of Autonomous Mobility On Demand. *Transp. Res. Rec. J. Transp. Res. Board* 2564, 21–30. <https://doi.org/10.3141/2564-03>
- Babicheva, T., Burghout, W., Andreasson, I., Faul, N., 2019. Empty vehicle redistribution and fleet size in autonomous taxi systems. *IET Intell. Transp. Syst.* 13, 677–682. <https://doi.org/10.1049/iet-its.2018.5260>
- Bansal, P., Kockelman, K.M., 2018. Are we ready to embrace connected and self-driving vehicles? A case study of Texans. *Transportation (Amst)*. 45, 641–675. <https://doi.org/10.1007/s11116-016-9745-z>
- Bansal, P., Kockelman, K.M., 2017. Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies. *Transp. Res. Part A Policy Pract.* 95, 49–63. <https://doi.org/10.1016/j.tra.2016.10.013>
- Bansal, P., Kockelman, K.M., Singh, A., 2016. Assessing public opinions of and interest in new vehicle technologies: An Austin perspective. *Transp. Res. Part C Emerg. Technol.* 67, 1–14. <https://doi.org/10.1016/j.trc.2016.01.019>
- Bauer, G.S., Greenblatt, J.B., Gerke, B.F., 2018. Cost, Energy, and Environmental Impact of Automated Electric Taxi Fleets in Manhattan. *Environ. Sci. Technol.* 52, 4920–4928. <https://doi.org/10.1021/acs.est.7b04732>
- Becker, F., Axhausen, K.W., 2017. Literature review on surveys investigating the acceptance of automated vehicles. *Transportation (Amst)*. 44, 1293–1306. <https://doi.org/10.1007/s11116-017->

9808-9

- Beirão, G., Sarsfield Cabral, J.A., 2007. Understanding attitudes towards public transport and private car: A qualitative study. *Transp. Policy* 14, 478–489. <https://doi.org/10.1016/J.TRANPOL.2007.04.009>
- Berckmans, G., Messagie, M., Smekens, J., Omar, N., Vanhaverbeke, L., Mierlo, J. Van, Berckmans, G., Messagie, M., Smekens, J., Omar, N., Vanhaverbeke, L., Van Mierlo, J., 2017. Cost Projection of State of the Art Lithium-Ion Batteries for Electric Vehicles Up to 2030. *Energies* 10, 1314. <https://doi.org/10.3390/en10091314>
- Bischoff, J., Francisco, J.M., Domingues-olavarr, G., Maciejewski, M., Nagel, K., 2019. Impacts of vehicle fleet electrification in Sweden – a simulation-based assessment of long-distance trips.
- Bischoff, J., Maciejewski, M., 2016a. Simulation of City-wide Replacement of Private Cars with Autonomous Taxis in Berlin. *Procedia Comput. Sci.* 83, 237–244. <https://doi.org/10.1016/J.PROCS.2016.04.121>
- Bischoff, J., Maciejewski, M., 2016b. Autonomous Taxicabs in Berlin – A Spatiotemporal Analysis of Service Performance. *Transp. Res. Procedia* 19, 176–186. <https://doi.org/10.1016/j.trpro.2016.12.078>
- Bischoff, J., Maciejewski, M., 2014. Agent-based Simulation of Electric Taxicab Fleets, in: *Transportation Research Procedia*. Elsevier, pp. 191–198. <https://doi.org/10.1016/j.trpro.2014.11.015>
- Bischoff, J., Maciejewski, M., Nagel, K., 2017. City-wide shared taxis: A simulation study in Berlin, in: *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, pp. 275–280. <https://doi.org/10.1109/ITSC.2017.8317926>
- Boesch, P.M., Ciari, F., Axhausen, K.W., 2016. Autonomous Vehicle Fleet Sizes Required to Serve Different Levels of Demand. *Transp. Res. Rec. J. Transp. Res. Board* 2542, 111–119. <https://doi.org/10.3141/2542-13>
- Bösch, P.M., Becker, F., Becker, H., Axhausen, K.W., 2018. Cost-based analysis of autonomous mobility services. *Transp. Policy* 64, 76–91. <https://doi.org/10.1016/j.tranpol.2017.09.005>
- Cano, Z.P., Banham, D., Ye, S., Hintennach, A., Lu, J., Fowler, M., Chen, Z., 2018. Batteries and fuel cells for emerging electric vehicle markets. *Nat. Energy* 3, 279–289. <https://doi.org/10.1038/s41560-018-0108-1>
- Castiglione, J., Bradley, M., Gliebe, J., 2015. Activity-Based Travel Demand Models: A Primer, SHRP 2 Report. National Academies Press. [https://doi.org/Strategic Highway Research Program \(SHRP 2\) Report S2-C46-RR-1](https://doi.org/Strategic Highway Research Program (SHRP 2) Report S2-C46-RR-1)
- Cerema, 2017. Enquête Ménages Déplacements 2017. Métropole Rouen Normandie. https://www.metropole-rouen-normandie.fr/files/tmp/2018-03-20_EMDROUEN_MRN_VDef.pdf.
- Chan, N.D., Shaheen, S.A., 2012. Ridesharing in North America: Past, Present, and Future. *Transp. Rev.* 32, 93–112. <https://doi.org/10.1080/01441647.2011.621557>
- Charypar, D., Nagel, K., 2005. Generating complete all-day activity plans with genetic algorithms. *Transportation (Amst)*. 32, 369–397. <https://doi.org/10.1007/s11116-004-8287-y>
- Chen, T.D., Kockelman, K.M., 2016. Management of a Shared Autonomous Electric Vehicle Fleet: Implications of Pricing Schemes. *Transp. Res. Rec. J. Transp. Res. Board* 2572, 37–46. <https://doi.org/10.3141/2572-05>
- Chen, T.D., Kockelman, K.M., Hanna, J.P., 2016. Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions. *Transp. Res. Part A Policy Pract.* 94, 243–254. <https://doi.org/10.1016/j.tra.2016.08.020>

- Church, R., ReVelle, C., 1974. The maximal covering location problem. *Pap. Reg. Sci. Assoc.* 32, 101–118. <https://doi.org/10.1007/BF01942293>
- Cohen, A., Shaheen, S., 2018. Planning for Shared Mobility. <https://doi.org/10.7922/G2NV9GDD>
- Conway, M., Salon, D., King, D., 2018. Trends in Taxi Use and the Advent of Ridehailing, 1995–2017: Evidence from the US National Household Travel Survey. *Urban Sci.* 2, 79. <https://doi.org/10.3390/urbansci2030079>
- DG Trésor [WWW Document], 2018. URL <https://www.tresor.economie.gouv.fr/>
- Fagnant, D.J., Kockelman, K., 2015. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transp. Res. Part A Policy Pract.* 77, 167–181. <https://doi.org/10.1016/j.tra.2015.04.003>
- Fagnant, D.J., Kockelman, K.M., 2018. Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. *Transportation (Amst)*. 45, 143–158. <https://doi.org/10.1007/s11116-016-9729-z>
- Fagnant, D.J., Kockelman, K.M., 2014. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. *Transp. Res. Part C Emerg. Technol.* 40, 1–13. <https://doi.org/10.1016/j.trc.2013.12.001>
- Farhan, J., Chen, T.D., 2018. Impact of ridesharing on operational efficiency of shared autonomous electric vehicle fleet. *Transp. Res. Part C Emerg. Technol.* 93, 310–321. <https://doi.org/10.1016/j.trc.2018.04.022>
- Farooq, B., Bierlaire, M., Hurtubia, R., Flötteröd, G., 2013. Simulation based population synthesis. *Transp. Res. Part B Methodol.* 58, 243–263. <https://doi.org/10.1016/j.trb.2013.09.012>
- Firnkorn, J., Müller, M., 2012. Selling Mobility instead of Cars: New Business Strategies of Automakers and the Impact on Private Vehicle Holding. *Bus. Strateg. Environ.* 21, 264–280. <https://doi.org/10.1002/bse.738>
- Gärling, T., Schuitema, G., 2007. Travel Demand Management Targeting Reduced Private Car Use: Effectiveness, Public Acceptability and Political Feasibility. *J. Soc. Issues* 63, 139–153. <https://doi.org/10.1111/j.1540-4560.2007.00500.x>
- Gawron, J.H., Keoleian, G.A., De Kleine, R.D., Wallington, T.J., Kim, H.C., 2018. Life Cycle Assessment of Connected and Automated Vehicles: Sensing and Computing Subsystem and Vehicle Level Effects. *Environ. Sci. Technol.* 52, 3249–3256. <https://doi.org/10.1021/acs.est.7b04576>
- Gkartzonikas, C., Gkritza, K., 2019. What have we learned? A review of stated preference and choice studies on autonomous vehicles. *Transp. Res. Part C Emerg. Technol.* 98, 323–337. <https://doi.org/10.1016/J.TRC.2018.12.003>
- Greenblatt, J.B., Saxena, S., 2015. Autonomous taxis could greatly reduce greenhouse-gas emissions of US light-duty vehicles. *Nat. Clim. Chang.* 5, 860–863. <https://doi.org/10.1038/nclimate2685>
- Greenblatt, J.B., Shaheen, S., 2015. Automated Vehicles, On-Demand Mobility, and Environmental Impacts. *Curr. Sustain. Energy Reports* 2, 74–81. <https://doi.org/10.1007/s40518-015-0038-5>
- Gurumurthy, K.M., Kockelman, K.M., 2020. Modeling Americans' autonomous vehicle preferences: A focus on dynamic ride-sharing, privacy & long-distance mode choices. *Technol. Forecast. Soc. Change* 150. <https://doi.org/10.1016/j.techfore.2019.119792>
- 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. *Transp. Res. Rec. J. Transp. Res. Board* 036119811985078. <https://doi.org/10.1177/0361198119850785>
- Haboucha, C.J., Ishaq, R., Shiftan, Y., 2017. User preferences regarding autonomous vehicles. *Transp. Res. Part C Emerg. Technol.* 78, 37–49. <https://doi.org/10.1016/j.trc.2017.01.010>

- Hao, M., Li, Y., Yamamoto, T., Hao, M., Li, Y., Yamamoto, T., 2019. Public Preferences and Willingness to Pay for Shared Autonomous Vehicles Services in Nagoya, Japan. *Smart Cities* 2, 230–244. <https://doi.org/10.3390/smartcities2020015>
- Heilig, M., Hilgert, T., Mallig, N., Kagerbauer, M., Vortisch, P., 2017. Potentials of Autonomous Vehicles in a Changing Private Transportation System – a Case Study in the Stuttgart Region. *Transp. Res. Procedia* 26, 13–21. <https://doi.org/10.1016/j.trpro.2017.07.004>
- Heilig, M., Mallig, N., Schröder, O., Kagerbauer, M., Vortisch, P., 2018. Implementation of free-floating and station-based carsharing in an agent-based travel demand model. *Travel Behav. Soc.* 12, 151–158. <https://doi.org/10.1016/j.tbs.2017.02.002>
- Henao, A., Marshall, W.E., 2019. The impact of ride hailing on parking (and vice versa). *J. Transp. Land Use* 12. <https://doi.org/10.5198/jtlu.2019.1392>
- Hörl, S., 2017. Agent-based simulation of autonomous taxi services with dynamic demand responses. *Procedia Comput. Sci.* 109, 899–904. <https://doi.org/10.1016/j.procs.2017.05.418>
- Hörl, S., Balac, M., Axhausen, K.W., 2018. A first look at bridging discrete choice modeling and agent-based microsimulation in MATSim, in: *Procedia Computer Science*. pp. 900–907. <https://doi.org/10.1016/j.procs.2018.04.087>
- Hörl, S., Erath, A., Axhausen, K.W., 2016. Simulation of autonomous taxis in a multi-modal traffic scenario with dynamic demand, *Arbeitsberichte Verkehrs- und Raumplanung*. IVT, ETH Zurich. <https://doi.org/10.3929/ETHZ-B-000118794>
- Hörl, S., Ruch, C., Becker, F., Frazzoli, E., Axhausen, K.W., 2019. Fleet operational policies for automated mobility: A simulation assessment for Zurich. *Transp. Res. Part C Emerg. Technol.* 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*. Ubiquity Press, London. <https://doi.org/10.5334/baw>
- Hyland, M., Mahmassani, H.S., 2018. Dynamic autonomous vehicle fleet operations: Optimization-based strategies to assign AVs to immediate traveler demand requests. *Transp. Res. Part C Emerg. Technol.* 92, 278–297. <https://doi.org/10.1016/J.TRC.2018.05.003>
- Iacobucci, R., McLellan, B., Tezuka, T., 2019. Optimization of shared autonomous electric vehicles operations with charge scheduling and vehicle-to-grid. *Transp. Res. Part C Emerg. Technol.* 100, 34–52. <https://doi.org/10.1016/j.trc.2019.01.011>
- Iacobucci, R., McLellan, B., Tezuka, T., 2018. Modeling shared autonomous electric vehicles: Potential for transport and power grid integration. *Energy* 158, 148–163. <https://doi.org/10.1016/J.ENERGY.2018.06.024>
- INSEE, 2018. Dossier complet Ile-de-France [WWW Document]. URL <https://www.insee.fr/fr/statistiques/2011101?geo=REG-11>
- International Energy Agency., 2018. *Global EV Outlook 2018*. International Energy Agency. <https://doi.org/10.1787/9789264302365-en>
- ITF, 2015. *Urban Mobility System Upgrade: How shared self-driving cars could change city traffic*. Int. Transp. Forum Policy Pap. <https://doi.org/10.1787/5jlwvzdk29g5-en>
- Jones, E.C., Leibowicz, B.D., 2019. Contributions of shared autonomous vehicles to climate change mitigation. *Transp. Res. Part D Transp. Environ.* 72, 279–298. <https://doi.org/10.1016/J.TRD.2019.05.005>
- Kamel, J., Vosooghi, R., Puchinger, J., 2018. Synthetic Population Generator for France. <https://doi.org/10.13140/RG.2.2.19137.81763>
- Kamel, J., Vosooghi, R., Puchinger, J., Ksontini, F., Sirin, G., 2019. Exploring the Impact of User Preferences on Shared Autonomous Vehicle Modal Split: A Multi-Agent Simulation Approach.

- Transp. Res. Procedia 37, 115–122. <https://doi.org/10.1016/j.trpro.2018.12.173>
- Kang, N., Feinberg, F.M., Papalambros, P.Y., 2016. Autonomous Electric Vehicle Sharing System Design. *J. Mech. Des.* 139, 011402. <https://doi.org/10.1115/1.4034471>
- Kent, J.L., 2015. Still Feeling the Car – The Role of Comfort in Sustaining Private Car Use. *Mobilities* 10, 726–747. <https://doi.org/10.1080/17450101.2014.944400>
- Krueger, R., Rashidi, T.H., Rose, J.M., 2016. Preferences for shared autonomous vehicles. *Transp. Res. Part C Emerg. Technol.* 69, 343–355. <https://doi.org/10.1016/j.trc.2016.06.015>
- Lavieri, P.S., Garikapati, V.M., Bhat, C.R., Pendyala, R.M., Astroza, S., Dias, F.F., 2017. Modeling Individual Preferences for Ownership and Sharing of Autonomous Vehicle Technologies. *Transp. Res. Rec. J. Transp. Res. Board* 2665, 1–10. <https://doi.org/10.3141/2665-01>
- Levin, M.W., Kockelman, K.M., Boyles, S.D., Li, T., 2017. A general framework for modeling shared autonomous vehicles with dynamic network-loading and dynamic ride-sharing application. *Comput. Environ. Urban Syst.* 64, 373–383. <https://doi.org/10.1016/j.compenvurbsys.2017.04.006>
- Liang, X., Correia, G.H. de A., van Arem, B., 2016. Optimizing the service area and trip selection of an electric automated taxi system used for the last mile of train trips. *Transp. Res. Part E Logist. Transp. Rev.* 93, 115–129. <https://doi.org/10.1016/J.TRE.2016.05.006>
- Litman, T., 2018. Autonomous Vehicle Implementation Predictions Implications for Transport Planning, Victoria Transport Policy Institute.
- Liu, J., Kockelman, K.M., Boesch, P.M., Ciari, F., 2017. Tracking a system of shared autonomous vehicles across the Austin, Texas network using agent-based simulation. *Transportation (Amst)*. 44, 1261–1278. <https://doi.org/10.1007/s11116-017-9811-1>
- Loeb, B., Kockelman, K.M., 2019. Fleet performance and cost evaluation of a shared autonomous electric vehicle (SAEV) fleet: A case study for Austin, Texas. *Transp. Res. Part A Policy Pract.* 121, 374–385. <https://doi.org/10.1016/j.tra.2019.01.025>
- Loeb, B., Kockelman, K.M., Liu, J., 2018. Shared autonomous electric vehicle (SAEV) operations across the Austin, Texas network with charging infrastructure decisions. *Transp. Res. Part C Emerg. Technol.* 89, 222–233. <https://doi.org/10.1016/j.trc.2018.01.019>
- Logtenberg, R., Pawley, J., Saxifrage, B., 2018. Comparing Fuel and Maintenance Costs of Electric and Gas Powered Vehicles in Canada.
- Lokhandwala, M., Cai, H., 2018. Dynamic ride sharing using traditional taxis and shared autonomous taxis: A case study of NYC. *Transp. Res. Part C Emerg. Technol.* 97, 45–60. <https://doi.org/10.1016/J.TRC.2018.10.007>
- Lu, M., Taiebat, M., Xu, M., Hsu, S.-C., 2018. Multiagent Spatial Simulation of Autonomous Taxis for Urban Commute: Travel Economics and Environmental Impacts. *J. Urban Plan. Dev.* 144, 04018033. [https://doi.org/10.1061/\(ASCE\)UP.1943-5444.0000469](https://doi.org/10.1061/(ASCE)UP.1943-5444.0000469)
- Lyft, 2018. Lyft Pass [WWW Document]. Help page. URL <https://help.lyft.com/hc/en-us/articles/360001993048>
- Maciejewski, M., 2016. Dynamic Transport Services, in: Horni, A., Nagel, K., Axhausen, K.W. (Eds.), *The Multi-Agent Transport Simulation MATSim*. Ubiquity Press, pp. 145–152. <https://doi.org/10.5334/baw.23>
- Maciejewski, M., Bischoff, J., Hörl, S., Nagel, K., 2017. Towards a Testbed for Dynamic Vehicle Routing Algorithms. Springer, Cham, pp. 69–79. https://doi.org/10.1007/978-3-319-60285-1_6
- Mallig, N., Kagerbauer, M., Vortisch, P., 2013. mobiTopp – A Modular Agent-based Travel Demand Modelling Framework. *Procedia Comput. Sci.* 19, 854–859. <https://doi.org/10.1016/J.PROCS.2013.06.114>

- Martinez, L.M., Correia, G.H.A., Viegas, J.M., 2015. An agent-based simulation model to assess the impacts of introducing a shared-taxi system: an application to Lisbon (Portugal). *J. Adv. Transp.* 49, 475–495. <https://doi.org/10.1002/atr.1283>
- Martinez, L.M., Viegas, J.M., 2017. Assessing the impacts of deploying a shared self-driving urban mobility system: An agent-based model applied to the city of Lisbon, Portugal. *Int. J. Transp. Sci. Technol.* 6, 13–27. <https://doi.org/10.1016/j.ijtst.2017.05.005>
- Menon, N., Barbour, N., Zhang, Y., Pinjari, A.R., Mannering, F., 2019. Shared autonomous vehicles and their potential impacts on household vehicle ownership: An exploratory empirical assessment. *Int. J. Sustain. Transp.* 13, 111–122. <https://doi.org/10.1080/15568318.2018.1443178>
- Meyer, J., Becker, H., Bösch, P.M., Axhausen, K.W., 2017. Autonomous vehicles: The next jump in accessibilities? *Res. Transp. Econ.* 62, 80–91. <https://doi.org/10.1016/J.RETREC.2017.03.005>
- Milakis, D., van Arem, B., van Wee, B., 2017. Policy and society related implications of automated driving: A review of literature and directions for future research. *J. Intell. Transp. Syst.* 21, 324–348. <https://doi.org/10.1080/15472450.2017.1291351>
- Moorthy, A., De Kleine, R., Keoleian, G., Good, J., Lewis, G., 2017. Shared Autonomous Vehicles as a Sustainable Solution to the Last Mile Problem: A Case Study of Ann Arbor-Detroit Area. *SAE Int. J. Passeng. Cars - Electron. Electr. Syst.* 10, 2017-01–1276. <https://doi.org/10.4271/2017-01-1276>
- Newman, P., Kenworthy, J.R., 2015. *The end of automobile dependence : how cities are moving beyond car-based planning.* Island Press, Washington, DC.
- Newman, P., Kenworthy, J.R., 1998. *Sustainability and cities : overcoming automobile dependence.* Island Press, Washington, DC.
- Nykvist, B., Nilsson, M., 2015. Rapidly falling costs of battery packs for electric vehicles. *Nat. Clim. Chang.* 5, 329–332. <https://doi.org/10.1038/nclimate2564>
- Ohde, B., Ślaski, G., Maciejewski, M., 2016. Statistical analysis of real-world urban driving cycles for modelling energy consumption of electric vehicles. *J. Mech. Transp. Eng.* 25–39. <https://doi.org/10.21008/j.2449-920X.2016.68.2.03>
- Ohnemus, M., Perl, A., 2016. Shared Autonomous Vehicles: Catalyst of New Mobility for the Last Mile? *Built Environ.* 42, 589–602. <https://doi.org/10.2148/benv.42.4.589>
- OMNIL, 2017. *Enquête globale transport - La mobilité en Île-de-France [WWW Document].* URL <http://www.omnil.fr/spip.php?article81>
- Ortuzar, J. de D., Willumsen, L.G., 2011. *Modelling Transport, Modelling Transport.* <https://doi.org/10.1002/9781119993308>
- Palmer, K., Tate, J.E., Wadud, Z., Nellthorp, J., 2018. Total cost of ownership and market share for hybrid and electric vehicles in the UK, US and Japan. *Appl. Energy* 209, 108–119. <https://doi.org/10.1016/J.APENERGY.2017.10.089>
- Quarles, N., Kockelman, K.M., Lee, J., 2019. America’s fleet evolution in an automated future.
- Redman, L., Friman, M., Gärling, T., Hartig, T., 2013. Quality attributes of public transport that attract car users: A research review. *Transp. Policy* 25, 119–127. <https://doi.org/10.1016/J.TRANPOL.2012.11.005>
- Renault, 2019. *Renault Zoe Technical Sheet [WWW Document].* URL <https://www.renault.fr/vehicules/vehicules-electriques/zoe/versions-et-prix.html>
- Scheltes, A., de Almeida Correia, G.H., 2017. Exploring the use of automated vehicles as last mile connection of train trips through an agent-based simulation model: An application to Delft, Netherlands. *Int. J. Transp. Sci. Technol.* 6, 28–41. <https://doi.org/10.1016/J.IJTST.2017.05.004>

- Shaheen, S., Cohen, A., Zohdy, I., 2016. Shared Mobility: Current Practices and Guiding Principles, U.S. Department of Transportation, Federal Highway Administration. Washington, D.C.
- Shaheen, S., Sperling, D., Wagner, C., 1998. Carsharing in Europe and North America: Past, Present, and Future. *Transp. Q.* 52, 35–52. <https://doi.org/10.1068/a201285>
- Shaheen, S.A., Chan, N.D., Micheaux, H., 2015. One-way carsharing's evolution and operator perspectives from the Americas. *Transportation (Amst)*. 42, 519–536. <https://doi.org/10.1007/s11116-015-9607-0>
- Shaheen, S.A., Cohen, A.P., 2007. Growth in Worldwide Carsharing. *Transp. Res. Rec. J. Transp. Res. Board* 1992, 81–89. <https://doi.org/10.3141/1992-10>
- 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. *Transp. Res. Part C Emerg. Technol.* 98, 167–185. <https://doi.org/10.1016/j.trc.2018.11.002>
- Soteropoulos, A., Berger, M., Ciari, F., 2019. Impacts of automated vehicles on travel behaviour and land use: an international review of modelling studies. *Transp. Rev.* 39, 29–49. <https://doi.org/10.1080/01441647.2018.1523253>
- Spieser, K., Treleaven, K., Zhang, R., Frazzoli, E., Morton, D., Pavone, M., 2014. Toward a Systematic Approach to the Design and Evaluation of Automated Mobility-on-Demand Systems: A Case Study in Singapore, in: *Road Vehicle Automation*. Springer, pp. 229–245. https://doi.org/10.1007/978-3-319-05990-7_20
- Steck, F., Kolarova, V., Bahamonde-Birke, F., Trommer, S., Lenz, B., 2018. How Autonomous Driving May Affect the Value of Travel Time Savings for Commuting. *Transp. Res. Rec. J. Transp. Res. Board* 036119811875798. <https://doi.org/10.1177/0361198118757980>
- Stocker, A., Shaheen, S., 2018. Shared Automated Mobility: Early Exploration and Potential Impacts, in: *Road Vehicle Automation 4*. pp. 125–139. https://doi.org/10.1007/978-3-319-60934-8_12
- Stoiber, T., Schubert, I., Hoerler, R., Burger, P., 2019. Will consumers prefer shared and pooled-use autonomous vehicles? A stated choice experiment with Swiss households. *Transp. Res. Part D Transp. Environ.* 71, 265–282. <https://doi.org/10.1016/j.trd.2018.12.019>
- Vahidi, A., Sciarretta, A., 2018. Energy saving potentials of connected and automated vehicles. *Transp. Res. Part C Emerg. Technol.* 95, 822–843. <https://doi.org/10.1016/J.TRC.2018.09.001>
- Vinet, L., Zhedanov, A., 2011. A 'missing' family of classical orthogonal polynomials. *J. Phys. A Math. Theor.* 44, 085201. <https://doi.org/10.1088/1751-8113/44/8/085201>
- Vosooghi, R., Kamel, J., Puchinger, J., Leblond, V., Jankovic, M., 2019a. Robo-Taxi service fleet sizing: assessing the impact of user trust and willingness-to-use. *Transportation (Amst)*. <https://doi.org/10.1007/s11116-019-10013-x>
- Vosooghi, R., Puchinger, J., Jankovic, M., Sirin, G., 2017. A critical analysis of travel demand estimation for new one-way carsharing systems, in: *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, pp. 199–205. <https://doi.org/10.1109/ITSC.2017.8317917>
- Vosooghi, R., Puchinger, J., Jankovic, M., Vouillon, A., 2019b. Shared autonomous vehicle simulation and service design. *Transp. Res. Part C Emerg. Technol.* 107, 15–33. <https://doi.org/10.1016/J.TRC.2019.08.006>
- Wang, B., Ordonez Medina, S.A., Fourie, P., 2018. Simulation of Autonomous Transit On Demand for Fleet Size and Deployment Strategy Optimization. *Procedia Comput. Sci.* 130, 797–802. <https://doi.org/10.1016/J.PROCS.2018.04.138>
- Wardman, M., Chintakayala, V.P.K., de Jong, G., 2016. Values of travel time in Europe: Review and meta-analysis. *Transp. Res. Part A Policy Pract.* 94, 93–111.

<https://doi.org/10.1016/J.TRA.2016.08.019>

- Webb, J., Wilson, C., Kularatne, T., 2019. Will people accept shared autonomous electric vehicles? A survey before and after receipt of the costs and benefits. *Econ. Anal. Policy* 61, 118–135. <https://doi.org/10.1016/j.eap.2018.12.004>
- Weiss, J., Hledik, R., Lueken, R., Lee, T., Gorman, W., 2017. The electrification accelerator: Understanding the implications of autonomous vehicles for electric utilities. *Electr. J.* 30, 50–57. <https://doi.org/10.1016/j.tej.2017.11.009>
- Weldon, P., Morrissey, P., O'Mahony, M., 2018. Long-term cost of ownership comparative analysis between electric vehicles and internal combustion engine vehicles. *Sustain. Cities Soc.* 39, 578–591. <https://doi.org/10.1016/J.SCS.2018.02.024>
- Wen, J., Chen, Y.X., Nassir, N., Zhao, J., 2018. Transit-oriented autonomous vehicle operation with integrated demand-supply interaction. *Transp. Res. Part C Emerg. Technol.* 97, 216–234. <https://doi.org/10.1016/J.TRC.2018.10.018>
- Yi, Z., Smart, J., Shirk, M., 2018. Energy impact evaluation for eco-routing and charging of autonomous electric vehicle fleet: Ambient temperature consideration. *Transp. Res. Part C Emerg. Technol.* 89, 344–363. <https://doi.org/10.1016/J.TRC.2018.02.018>
- Zhang, R., Rossi, F., Pavone, M., 2016. Model predictive control of autonomous mobility-on-demand systems, in: 2016 IEEE International Conference on Robotics and Automation (ICRA). IEEE, pp. 1382–1389. <https://doi.org/10.1109/ICRA.2016.7487272>
- Zhang, T., Chen, X., Yu, Z., Zhu, X., Shi, D., 2018. A Monte Carlo Simulation Approach to Evaluate Service Capacities of EV Charging and Battery Swapping Stations. *IEEE Trans. Ind. Informatics* 14, 3914–3923. <https://doi.org/10.1109/TII.2018.2796498>
- Zhang, W., Guhathakurta, S., Fang, J., Zhang, G., 2015a. The Performance and Benefits of a Shared Autonomous Vehicles Based Dynamic Ridesharing System: An Agent-Based Simulation Approach, in: Transportation Research Board 95th Annual Meeting. Washington DC, United States.
- Zhang, W., Guhathakurta, S., Fang, J., Zhang, G., 2015b. Exploring the impact of shared autonomous vehicles on urban parking demand: An agent-based simulation approach. *Sustain. Cities Soc.* 19, 34–45. <https://doi.org/10.1016/J.SCS.2015.07.006>
- Zhao, Y., Kockelman, K.M., 2018. Anticipating the Regional Impacts of Connected and Automated Vehicle Travel in Austin, Texas. *J. Urban Plan. Dev.* 144, 04018032. [https://doi.org/10.1061/\(ASCE\)UP.1943-5444.0000463](https://doi.org/10.1061/(ASCE)UP.1943-5444.0000463)
- Zheng, H., Son, Y.-J., Chiu, Y.-C., Head, L., Feng, Y., Xo, H., Kim, S., Hickman, M., 2013. A Primer for Agent-Based Simulation and Modeling in Transportation Applications, Federal Highway Administration.

Titre : Conception, modélisation et simulation des services Robot-Taxi

Mots clés : Robot-Taxi, mobilité partagée, population synthétique, système multi-agents

Résumé : Les Robot-Taxis constituent la prochaine évolution majeure de la mobilité urbaine. Cette technologie intéresse certains constructeurs automobiles qui envisagent de jouer le rôle des entreprises de transport. Ceci leur permet de développer un modèle d'affaire basé sur des revenus par kilomètre et par trajet. Un service basé sur des véhicules autonomes a l'avantage de pouvoir fusionner des systèmes de service de taxis classiques à la demande et de voitures en libre-service. Ainsi ce service de transport unifié offre une forme de mobilité partagée plus accessible, dynamique et intelligente. Le succès et la compétitivité des futurs services de Robot-Taxis dépendent de leurs modèles opérationnels, qui sont intrinsèquement liés à la configuration du service et aux spécifications de la flotte. En utilisant une approche complète de modélisation du service Robot-Taxi dans un système multimodal en valorisant la demande dynamique et la variation de préférences des voyageurs, cette thèse vise

à évaluer les performances de diverses flottes de Robot-Taxi et leurs configurations opérationnelles. Pour cela, d'abord, différentes approches de la modélisation de la demande de déplacement de Robot-Taxi ainsi que des techniques de simulation sont passées en revue et analysées. Ensuite, les données et processus requis, en particulier la génération de la population synthétique et l'allocation de la chaîne d'activités, sont investigués. Conformément aux objectifs de cette thèse, un cadre général de modélisation et de simulation de services Robot-Taxi est proposé. Ensuite, l'impact de préférences des usagers sur la conception du service Robot-Taxi, et en particulier, sur le dimensionnement de la flotte est exploré. Des analyses approfondies des performances du service, considérant la taille de flotte, la capacité du véhicule, le partage de parcours et le repositionnement, le coût du service sont ensuite réalisées. Enfin, en considérant une flotte de véhicules autonomes électriques, l'impact des infrastructures de recharge sur l'efficacité du service sont explorés.

Title: Shared autonomous vehicle service design, modeling, and simulation

Keywords : shared autonomous vehicles, synthetic population, multi-agent simulation, service design

Abstract: Shared autonomous vehicles (SAVs) are the next major evolution in urban mobility. This technology has attracted much interest of car manufacturers aiming at playing a role as transportation network companies (TNCs) and carsharing agencies in order to gain benefits per kilometer and per ride. An SAV service can merge cabs, carsharing, and ridesharing systems into a single transportation mode, and allow a more accessible, dynamic, and intelligent form of shared mobility. However, the success and competitiveness of future SAV services depend on their operational models, which are linked intrinsically to the service configuration and fleet specification. On the other hand, any changes in operational models of SAVs result in different demands for such a service in a real-world transportation network. Hence, considering the dynamic interaction of service and demand represents a key-factor for successfully designing SAVs in a real-life context. Using a comprehensive framework of SAV simulation in a multimodal dynamic-demand

system with integrated SAV user taste variation, this thesis evaluates the performance of various non-electric and electric SAV fleets and their operational configuration, and to design the service. In this context, first, different approaches to SAV travel demand modeling and simulation techniques are reviewed and analyzed. Next, the required data and process, particularly synthetic population generation and activity chain allocation, are investigated. In line with the purpose of this thesis, an overall framework of comprehensive SAV modeling and simulation is then proposed. Later, the impact of user taste variation on SAV service design and particularly fleet size is explored. Insights gained through a comprehensive investigation of SAV service performance considering fleet size, vehicle capacity, ridesharing and rebalancing, and service cost along with proposed key performance indicators are then provided. Finally, assuming a fleet of electric SAVs, the impacts of charging infrastructure on service efficiency are explored.

