Karlsruhe Institute of Technology

Sustainability of Autonomous Vehicles: An Agent-based Simulation of the Private Passenger Sector

Master Thesis

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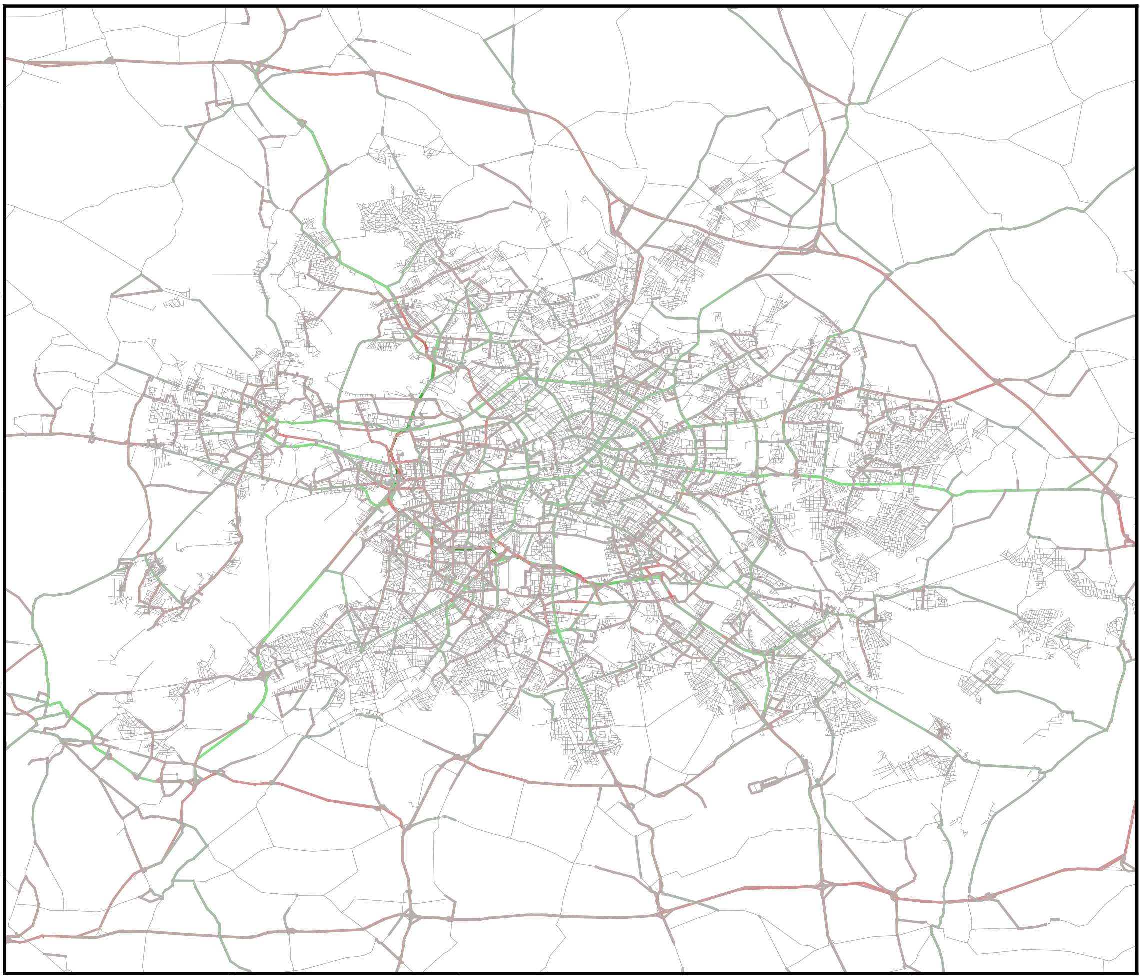

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Abstract

Initiatives such as the European Green Deal establish mandatory objectives for climate neutrality by 2050. To realize this, predominant sectors like the transportation industry necessitate substantial improvements in emission efficiency, as transportation accounts for 20% of global CO_2 emissions. Remarkably, 41% of that are attributed to passenger transport alone. Amidst technological progression, shared autonomous vehicles (SAV) are projected to be a vital instrument in reducing greenhouse gas emissions in the private passenger sector. Hence, this study investigates the potential sustainability advantages of SAV introduction to the private passenger car sector.

We draw upon an agent-based simulation model to avoid building upon theoretic populations and generic simulation approaches, not appropriately allowing to derive realistic SAV simulations. Agent-based simulations account for individual agent optimisation and are posed to be especially applicable to model traffic. More precisely, we build upon a calibrated model which incorporates real world commuter and travel statistics of Berlin. As current research frequently uses outdated travel data, this study generates a projection of three levels of travel demand of the wider area of Berlin in 2050. Additionally, we identify the need for more research on sustainability effects considering multiple levels of potential SAV introduction, as AV and SAV adoption is associated with high uncertainty. Regulatory interventions posed to be a solution to steer SAV adoption effectively. Therefore, we introduce three levels of SAV-exclusive car-based traffic zones in our simulation scenarios. The three level of zones range from the inner city of Berlin to the entire simulation, including Berlin and Brandenburg. Lastly, we identify the need for more comprehensive sustainability analyses, focusing on more than single parameters such as tailpipe emissions. Consequently, we compare driving-related emissions and energy consumption as well as the total expected life-cycle greenhouse gas impact of all SAV introduction and demand forecasting scenarios.

Our findings reveal that SAV introduction increases the total passenger travel duration up to 62.1% and the passenger travel distance of up to 15.2% due to added wait time and detours. This effect is particularly noticeable in large SAV-exclusive zones. However, occupancy rates increase simultaneously, causing total vehicles kilometers to stay consistent. We observe an initial rise of 0.8% to 2.8% in vehicle kilometers considering an unchanged population, while smaller SAV-exclusive zones see the highest increase. In turn, when including our travel demand forecast which accounts for increased population size and travel density, SAV introduction reduces total vehicle kilometers by 0.5% to 3.6%, related to higher SAV occupancy. Lastly, accounting for SAV-related efficiency increases, we conclude savings in total life-cycle CO_2 emissions ranging from 0.4% to 9.6% and energy consumption ranging from 1.5% to 12.2% across all scenarios. When combined with a fully electric SAV fleet, the potential for emission reduction increases to 59.0%, and for energy consumption reduction to 74.7%.

Contents

1 Introduction

The European Union aims to lead global climate activities as worldwide greenhouse gas emissions across various sectors, including transportation, continue to rise [35]. Therefore, agreements such as the European Green Deal [50] introduce binding targets for climate neutrality until 2050 [35]. Consequently, major sectors like the transport industry, accounting for 20% of worldwide CO_2 emissions, require emission efficiency increases [43]. 41% of that is attributed to passenger transport only [77]. While some analyses of autonomous vehicle (AV) introduction raise concern about the negative sustainability impact based on increased computing power demand or increase in total distance traveled [33, 125], there is also the perspective that AVs can be a key lever to reduce overall emissions [52, 105, 115]. By increasing driving efficiency, reducing the number of required cars and improving the traffic flow, sustainability gains such as emission reduction, land, water, and biodiversity improvements, as well as noise and light pollution, can potentially be achieved [88, 119]. As these gains heavily depend on AV adoption scales, shared mobility acceptance, and the interaction with other modes of transport [119], this thesis analyzes the potential sustainability impacts of AVs, particularly shared AVs (SAVs), using scenarios of different SAV introduction through an agent-based simulation.

In current research, various agent-based simulations of SAVs have been conducted in order to analyze implications on traffic within cities (e.g., [20, 70, 98, 142]). Several studies derive sustainability implications (e.g., [58, 66, 134]), however, predominantly focusing on single sustainability indicators such as fuel efficiency or traffic-based emissions. Consequently, the demand for a more holistic evaluation of sustainability impacts from SAV introduction can be derived. Another common issue describes the fact that such analyses often build upon outdated simulation data [68] (e.g., [47, 92, 130, 145, 147]). Hence, it is crucial to incorporate travel demand forecasts to make analyses more realistic (e.g., [13, 36, 62, 68]). This study supports narrowing the realism gap by initially generating a demand projection of traffic in the broader Berlin area until 2050. Lastly, similar papers have already stated the fact that, next to technological development, policy trends describe one crucial aspect determining long-term adoption of AVs [12, 26, 54, 61]. As a result, we incorporate regulatory interventions in our simulations. More precisely, we analyze Berlin's future private transport sector and introduce three scales of mandatory SAV traffic zones in which private cars are not allowed to enter. These SAV-only zones range from the inner city of Berlin to a 100% SAV traffic scenario of the wider Berlin area. All implementation and processing related code can be found in our Git repository. [1]

[1] `https://github.com/daniel-bogdoll/agent_based_av`

1.1 Research Objective

This study combines agent-based simulations, a travel demand forecast for 2050 and potential regulatory interventions in order to derive SAV adoption scenarios while analyzing holistic sustainability implications of SAVs. The methodology of an agent-based simulation, building upon the multi-agent transport simulation (MATSim) [131], is explicitly useful as it provides an environment to realistically modify future passenger travel while incorporating behavior changes that otherwise would be difficult to estimate in advance [110]. Consequently, the following three research questions guide our analysis:

- What approaches and inputs for the scenario models of SAV simulations can be derived from literature?
- How can various scales of SAV introduction in the private passenger transport sector be realized using an agent-based simulation?
- How can the different SAV scenarios be evaluated and how do they perform in direct comparison, particularly in regards to sustainability impacts?

1.2 Overview of the Thesis

Initially, Chapter 2 provides an introduction to the simulation framework MATSim as background to build upon in the following Chapters. Chapter 3 presents an overview of the relevant literature and highlights the addressed research gap of this study. Chapter 4 outlines the methodology for addressing the research questions and for evaluating the results. To facilitate the understanding of the simulation's requirements and our adjustments, Chapter 5 outlines the experiment set up and data preprocessing and postprocessing in detail. The simulation results, along with the associated sustainability implications, are presented and evaluated in Chapter 6. This includes contrasting our findings with comparable results of other scholars. We conclude our work by outlining limitations of our analysis and suggestions for future research in Chapter 7.

2 Background

In the following, a basic introduction into agent-based simulations (see Section 2.1), the MATSim simulation framework (see Section 2.2), the specifications of the SAV traffic simulation (see Section 2.3) and the chosen Open-Source Berlin Scenario (see Section 2.4) is being provided. While research question one is being discussed more thoroughly in Chapter 5, the following descriptions build a first baseline towards approaches and inputs of SAV traffic simulations.

2.1 Agent-Based Simulations

According to Moon and Young [107], there are three main categories of traffic simulations: agent-based modeling, discrete-event modeling, and system dynamics modeling. The agent-based bottom-up approach involves the creation and analysis of frameworks constructed of agents (e.g., travelers) that interact within an environment (e.g., travel between destinations using various transport modes) in order to generate a simulation [55]. Discrete event simulations model systems bottom-up as well, but use an ordered sequence of events as the basic element [107]. Simulations are being generated by tracking state changes from specific events, like modeling a car rental desk to estimate customer wait times while the mentioned state changes can be represented by customers arriving [91]. Contrary to the two, the system dynamics method uses a top-down approach [107]. It sees a simulation as one big unit, similar to a city's overall traffic inflow and outflow, illustrating how the system changes and adjusts constantly [124]. System dynamic models derive simulations from a more holistic perspective [107]. Widely adopted tool examples to implement the three simulation categories are depicted in Table 2.1. MATSim in particular, as the baseline of our simulations, will be outlined in the following Section 2.2.

Nr.	Agent-based	Discrete-event	System dynamics
1	MATSim	Arena 10	Vensim
2	SimMobility	Quest 2	Powersim
3	AnyLogic	AutoMod	Stella

Table 2.1: Overview of widely adopted tools per simulation model category [83, 94, 107].

2.2 The Simulation Platform MATSim

The subsequent descriptions and exemplary illustrations of the simulation framework are based on the official MATSim handbook by Horni et al. [131].

MATSim is a Java-based, open-source simulation framework that simulates a population of agents conducting activities and movements. In case of MATSim, agents represent individuals that have specific daily travel plans. The simulation represents one day of traffic. While each simulation is initialized by predefined agent travel plans and set variables, such as traffic mode, departure time and locations, agents can modify their plans. Modifications involve adjusting modes, routes, or the activity duration in order to increase a score that represent an individual utility evaluation of the daily travel plans for each agent. Default traffic modes include for instance car travel, ride-sharing, walking, bicycle travel and public transport. The travel mode ride refers to an agent traveling as a passenger, not a driver, in a private car. The use of each traffic mode is associated with specific utility or cost values, such as fixed constants (e.g., associated with car ownership) and variable constants (e.g., associated with fuel consumption).

Intended for large-scale scenarios, such as large cities and metropolitan areas, MATSim focuses on parallelised handling of simulations. In MATSim agents optimize their activity schedules in regards to individual utility (e.g., choosing the best transport mode) until convergence is reached. The framework further allows agents to modify travel times and included destinations of travel plans. In the following, we outline two of the above mentioned concepts, relevant for our simulation: the traffic flow model and the co-evolutionary algorithm.

Traffic flow model. Per default MATSim incorporates the internal mobility simulation QSim, which utilizes a queue-based approach to simulate traffic. This method involves adding cars to a waiting queue when they enter a road segment and releasing them when the threshold of entering cars is not exceeding the road capacity. The traffic flow model in MATSim relies heavily on storage capacity and flow capacity. Flow capacity refers to the rate at which a link, representing a street or traffic line for public transport, can discharge vehicles per time interval, whereas storage capacity determines the maximum number of cars that can be accommodated on a network link.

Co-evolutionary algorithm. Initially, it is crucial to distinguish between evolutionary and co-evolutionary algorithms. Evolutionary algorithms aim for the best overall outcome using a general fitness measure, while co-evolutionary algorithms focus on improving individual plans for each agent to achieve convergence. Each person within the overall population is depicted through plans, and serves as an agent in the system. The co-evolutionary algorithm, as depicted in Figure 2.1, initially executes agents' plans (e.g., agents traveling in-between destinations of the simulation environment). Following that, plans are evaluated based on their total utility scoring. A portion of the agents, around 10%, is permitted to duplicate and adapt the chosen plan. This includes finding ideal routing alternatives or randomly changing traffic modes or travel times. Convergence is reached if agents cannot significantly improve their plans.

2.3 Simulation Extension for SAV Traffic

A variety of extensions have been realised to enhance the capabilities of MATSim [131]. One example describes the Dynamic Vehicle Routing Problem (DVRP) extension and its application to model demand-responsive transport (DRT) problems [21, 103]. While DVRP originally aims to simulate complex vehicle routing [103], the DRT module is used to incorporate the simultaneous

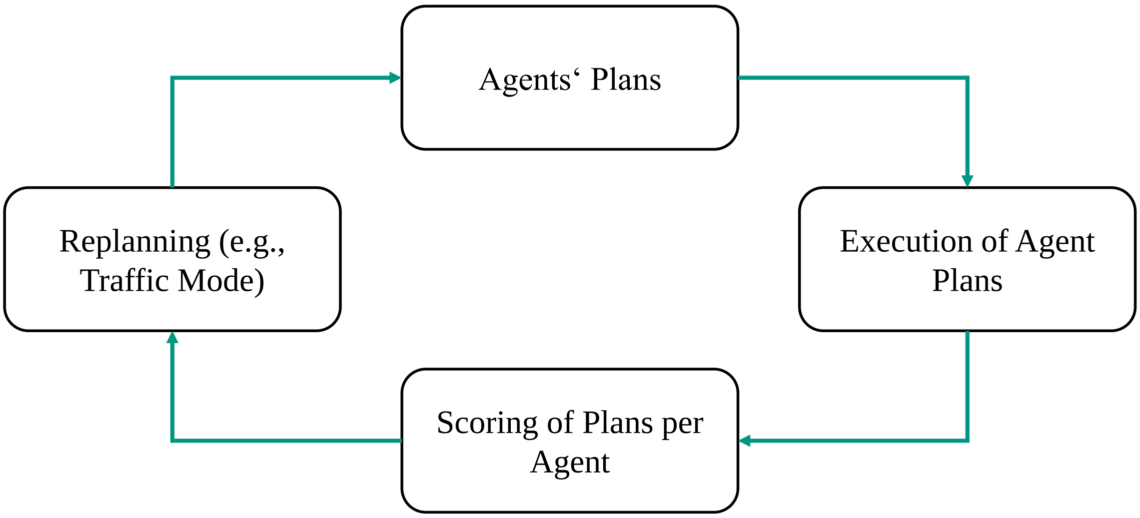


Figure 2.1: Representation of the co-evolutionary algorithm of MATSim adapted from Horni et al. [131].

transportation of agents with different destinations into MATSim [21]. Furthermore, the DRT module has been employed in numerous studies to incorporate SAVs [84, 92, 95, 102, 130]. The following descriptions are based on Bischoff et al. [21].

Model. The modeling of SAV traffic through the DRT module involves immediate SAV requests and a fleet of vehicles managed by a central dispatch system. Customers submit requests at the moment of departure, specifying pickup and drop-off locations. Each request has a fixed waiting time, while the total travel time must be kept under a given threshold. Requests can only be rejected immediately after submission. The service is ensured once it is scheduled. Vehicles have capacities, locations, and time windows for operation. They follow routes with stops for pickups and drop-offs while stops must have at least one passenger getting in or out, and the vehicle's capacity cannot increase between stops. After completing all stops, vehicles remain idle until a new dispatch occurs. This means vehicles by default do not enter traffic again nor drive back to a specific location, such as vehicle hubs.

Routing algorithm. The routing algorithm used in the SAV system employs a heuristic searching for insertions in vehicle routes when new requests are submitted while reducing detours and increasing service availability [103]. Consequently, the total time spent on handling requests is minimized. Feasible insertions comply with wait and travel time constraints as well as vehicle time windows. The algorithm selects the insertion with the smallest workload increase. Given the low demand for computer resources it provides good results. Lastly, the initial distribution of the SAVs plays a pivotal role in simulation outcomes, demanding careful consideration [23]. Per default, and after running the initial start up iteration, SAVs will be located at the same link as the last drop-off on the previous day.

2.4 The Open-Source Berlin Scenario.

After getting a better understanding for the general approach of traffic simulation using MATSim and the DRT module enabling the simulation of SAVs, we now outline our specific model that we build upon in our work. While there are various calibrated MATSim models designed to be used for traffic analysis of various cities and locations, such as Paris, Singapore and Toronto [106], our simulation draws upon the Berlin Scenario [146]. The following explanations are based on Ziemke et al. [146].

The MATSim Open Berlin scenario builds upon several creation steps that include: the derivation of a synthetic population, preparing input data using the Comprehensive Econometric Microsimulator for Daily Activity-Travel Patterns (CEMDAP) tool [18], generating activity-travel patterns using CEMDAP and calibrating MATSim. For instance, during the calibration step, the transport mode choices are reviewed to obtain suitable plans using the Calibration of Dynamic Traffic Simulations (CaDyTS) [51]. While each step will be detailed in the following, we initially provide an overview of the underlying data sources of this process in Table 2.2.

Input for the Berlin Scenario	Sources
A nation-wide census of Germany	Zensus 2011 [122]
Commuter statistics	Pendlerstatistik 2010 [29]
Geographical street map data	OpenStreetMap [112]
Local GTFS data	Verkehrsverbund Berlin Brandenburg [129]
Other traffic data (e.g. freight)	Bundesanstalt für Straßenwesen [30]
Shapefiles for municipality geometries	Copernicus Land Monitoring Service [37]
Travel surveys for validation	Technical Report TU Dresden [4] Infas and DLR Report [75]

Table 2.2: Overview of sources for the generation of the Open Berlin Scenario as in Ziemke et al. [146].

Initial population of Berlin agents. The scenario population is derived from the Zensus 2011 data [122], specifically targeting individuals aged 18 and above from Berlin and Brandenburg while offering information on population such as gender, age groups, employees and students. Additional data on employee workplaces is obtained from the 'Pendlerstatistik 2009' commuter statistics [29]. To ensure compatibility between commuter statistics and the census, a scaling procedure is applied, adjusting commuter numbers between municipalities. This ensures the total number of commuters matching the number of employed residents per specific zone. The generation process itself assigns age and gender based on census data, and home locations within Berlin's neighborhood-oriented zones to each generated person. Additionally, employment and school locations are randomly assigned per person using the commuter information. The generated information is then formatted according to CEMDAP's requirements.

Application of CEMDAP to generate agent activity patterns. After the generation of agents, CEMDAP is employed to assign daily activity-travel patterns to these individuals. Therefore, CEMDAP assumes comparable preferences among individuals with similar demographics in different regions based on its Los Angeles implementation. The software generates multiple initial activity-travel patterns for each agent, which are then evaluated using the MATSim transport simulation [131] to select patterns that align with real-world traffic data. By utilizing CEMDAP, initial daily activity-travel patterns are generated for each individual in the synthetic population. A sample of 10% of the total population is used for the final simulation. The output provides detailed descriptions of individuals' daily activities and trips.

Further calibrations of the agent plans. Additional calibrations to increase the realism of the simulation are being made. Since MATSim requires the selection of microscopic home and work locations, the randomly chosen coordinates are exclusively chosen when falling within suitable land use areas based on land cover data [37]. In order to include more relevant traffic types, freight traffic is added in the simulation based on simplified data from major arterials. However, the freight agents are excluded from the location choice calibration. Next to freight traffic, the MATSim simulation framework utilizes the GTFS dataset for the Berlin-Brandenburg region [129] to incorporate public transport (including schedules and vehicle properties). Moreover, real-world traffic observations are provided from multiple count stations and calibrated against traffic created by the MATSim simulation. This process involves running MATSim with CaDyTS to match traffic counts. A calibration effect is incorporated into MATSim's scoring of plans, evaluating their compatibility with real-world travel patterns which leads to changes in the final plans. Additionally, since the plans are limited to the 10% Open Berlin Scenario, traffic capacity is reduced accordingly. Finally, a calibration process (without CaDyTS) is carried out. Agents can change their transport modes, departure times, and routes depending on an agents' scores (based on time- and distance related travel cost and the activity times). Moreover, agents have the capability to adjust their departure times within a time window of two hours. This step additionally includes adjusting parameters and settings for mode-specific choices.

3 State of the Art

Alongside with latest sustainability-driven developments in politics and industry, particular research attention to the field of AV demand modeling and simulation can be identified [16, 56, 130]. Relevant to this study, we want to deep dive into three interconnected areas of research body, being the forecasting of potential AV and overall travel demand (see Section 3.1), agent-based simulations of AV and SAV traffic (see Section 3.2) as well as sustainability implications derived from the AV and SAV simulations (see Section 3.3).

To gather relevant papers, we initially conduct a literature review, according to Webster and Watson [132] and Brocke et al. [25], targeting the general research body of agent-based simulations of AVs and SAVs in April of 2023. We search databases, depicted in Table 3.1, using the keyword:

> "((simulat* OR agent-based OR model*) AND (autonom* OR self-driv* OR driverless OR self-pilot* OR unmanned) AND (AV OR SAV OR vehicle OR car OR driv* OR auto* OR taxi))"

While the initial search concludes 1,002 papers, we exclude irrelevant papers based on their title to reaching a focused list of 113 papers. We further exclude papers published before 2013. Based on their abstracts, we only include those that discuss AVs or SAVs. This results in a total of 39 papers, including nine papers derived from forward and backward search, as listed in Table 3.1.

Database	Number of Relevant Papers
ScienceDirect/Scopus	16
Forward & Backward Search	9
ProQuest	4
IEEEXplore	3
Taylor & Francis	3
Google Scholar	2
Springerlink	2
ACM Digital Library	0
KIT Online Library	0
Total	39

Table 3.1: Overview of the searched databases and relevant papers.

While the list of papers includes research addressing AV forecasts and sustainability impacts, we enhance this review to derive insights of both sub-fields using additional keyword as well as forward and backward searches. We replace "((simulat* OR agent-based OR model*)" of our keyword search either by "(forecast* OR prognos* OR futur*)" or "(emission* OR sustain* OR environment* OR energy)". An overview of considered papers can be found in the Appendix in

Section 8.1. In the following, we outline the current research body based on the most relevant papers.

3.1 Travel Demand Forecast

In examining the research landscape of AV and overall travel demand forecasting, it is important to differentiate between three distinct forecasting stages. Firstly, there are simulations of future AV demand analyses incorporating outdated travel data. Secondly, there are papers discussing the derivation of general travel demand forecasts. Lastly, we can identify studies focusing on the analysis of the AV adoption specifically, while disregarding the changes in overall travel demand.

Simulations of AV forecasts based on outdated travel data. It is evident that a significant proportion, particularly in agent-based simulations, relies on considerably outdated inputs, not taking into consideration any forecasts (e.g. [47, 92, 130, 145, 147]). However, for a more realistic representation of AVs, a time-frame encompassing 2030 or beyond is commonly assumed in literature (e.g. [13, 36, 96]). Consequently, the foundational assumptions of these simulations could undergo profound changes before the envisioned scenarios can even be realized, necessitating a reevaluation of the associated sustainability impacts. This becomes especially important given the state of AVs which face challenges of core traffic interaction [27], indicating a wide adoption to be difficult in the near future.

General travel forecasts. Accounting for changes in the overall travel demand, Cokyasar et al. [36] analyzed the energy usage and mobility implications of AVs level 4 and 5 in 2025 and 2040. They incorporated basic population growth, vehicle type changes, and technology improvement as factors for travel demand changes. Hidaka and Shiga [68] similarly consider multiple factors in order to predict future travel demand. These factors include changes in age compositions, age-related declines in individual travel needs, increasing rates of driver's license relinquishment, and regional factors. The combination of all inputs are used to forecast the demand for new mobility services employing SAVs and privately owned AVs.

The national road traffic projections of the UK department of transport [40] showcases the forecasting overall travel demand comes with significant uncertainty. While assuming a total of eight different traffic scenarios the highest increase was 54.2% above the most conservative prediction of almost unchanged travel demand [40]. By assuming this range of scenarios, general uncertainty can be incorporated.

AV forecasts not assuming any changes in overall travel demand. Bansal and Kockelman [13] conducted a forecast on the relative share of AV traffic within the overall private light-duty vehicle fleet of the United States (neglecting general travel demand developments). Their findings indicate that, under the assumption of a 10% annual increase in consumer willingness to pay and a 10% annual decrease in prices, a level 4 AV penetration rate of 87.2% is projected for the year 2045. This rate falls to 24.8% if willingness to pay and price changes are equal to 5%. As a result, considering the impracticality of such substantial price reductions or willingness to pay escalations of the 10% scenario, Bansal and Kockelman [13] assert that regulatory interventions promoting or mandating the use of AVs will be crucial.

Bischoff and Maciejewski [20] and Brownell and Kornhauser [28] assume that the introduction of SAVs particularly could change travel behavior leading to high shares of SAV travel. This is for instance caused by cost and potential time savings, assuming the benefits of SAVs are realized [27]. Additionally, being a lucrative business [46] describes an incentive for SAV operators to promote technology adoption, which in turn affects consumer behavior. A similar incentive to push SAV adoption holds true for cities as they benefit from reduced parking spaces demand of SAVs, making cities more attractive to live in [70].

In contrast to that, Pakusch et al. [113] and Harb et al. [63] doubt that car ownership will become an outdated model. Private passenger transport could continue to be the preferred mode of travel and SAVs would rather be adopted to the expense of public transport, leading to a smaller overall SAV share [113]. This emphasizes the difficulty of deriving plausible SAV scenarios as their adoption is dependent on the underlying assumptions and concept of how SAVs are introduced. In turn, not implementing external interventions leads to increased uncertainty when forecasting AV and SAV adoption.

Dubey et al. [42] incorporated more consumer behavior oriented factors (such as social network effects, risk aversion, the purchase price of autonomous vehicles, and safety measures/regulations) to forecast the relative adoption of AVs in Nashville, United States until 2050. The concept of incorporating forecasts into traffic analyses, provides valuable insights into AV adoption and variables that influence it.

In summary, current agent-based simulations frequently observe the adoption of AVs using outdated travel demand data [68], implying limited realism. Additionally, variations in AV adoption rates can be identified in current research while the concept of AV and SAV adoption is based on yet unclear dynamics, such as the idea of car ownership not getting outdated [113]. Introducing policy regulations are stated to be a relevant option to steer SAV use directly [13] and with that better predict AV adoption rates. Lastly, we find that uncertainties in overall demand forecasts and the variety of influences require considering multiple alternatives to account for a wide range of potential developments.

3.2 Agent-Based AV and SAV Simulations

While numerous approaches for traffic simulations exist, as stated in Chapter 2, our focus for this study lies on agent-based simulations. They provide a flexible and intuitive approach [15] to model systems which are optimised based on agents actions within an environment [55], such as SAV traffic being simulated by individual travel demand and not just overall traffic. In regards to agent-based simulation tools, a clear tendency towards MATSim as the main AV simulation platform can be identified. In the literature reviews of Li et al. [94] and Jing et al. [83] MATSim accounted for 46% of the simulation platforms in the analyzed research papers. The current research body on agent-based SAV simulations, mostly using MATSim, is outlined in the following.

Fagnant et al. [45] measure the impacts of SAVs on fleet efficiency and emission generation through the use of an undefined agent-based modeling platform and an artificial grid area as the simulation network. In their simulation all artificial travel plans (including all travel modes) are handled by a SAV fleet [45]. A main conclusion describes the overall beneficial environmental effects of SAVs due to the reduced number of vehicles overcompensating an increase of 10% in traffic occurrence. Although the theoretical approach of Fagnant et al. [45] and the handling of all traffic by a SAV fleet implies limited realism, their analysis indicate a promising approach to derive sustainability gains through 100% SAV adoption.

Liu et al. [98] introduce SAV travel to the city of Austin, Texas, in a MATSim-based analysis by applying various pricing fares, from 0.5 dollar to 1.25 dollar per mile of SAV usage. Based on that, they derive scales of SAV adoption ranging from 9.2% to 50.9%, relative to all mode trips [98]. Consequently, they introduced SAVs dynamically while concluding that especially long-distance traveler prefer SAVs over privately owned cars [98]. Additionally, they observe a shift from e.g., public transport, to SAV travel in case households do not own a private car [98]. Another finding from Liu et al. [98] is that the relative increase in distance traveled decreases with a higher share of SAV adoption, while emission reduction increases. This makes the alternative of a 100% SAV scenario particularly interesting.

Ziemke and Bischoff [145] measure accessibility implications of SAVs under different regulatory scenarios for the MATSim Open Berlin scenario [146]. For their simulation the DRT extension of MATSim is used while single-passenger SAV service is assumed, meaning passengers do not share rides, just the overall vehicle fleet [145]. Moreover, the regulatory intervention is implemented by conducting multiple simulations where a random 10% of agents that previously used public transport are now transitioned to SAVs [145]. They conclude SAVs to have positive effects on accessibility compared to public transport, underlining the benefits of SAVs [145]. Consequently, the approach of regulatory intervention to simulate partial SAV adoption can be seen as promising, although in this analysis limited to the 10% of the public transport sector per simulation.

Zwick et al. [147] analyze the implications of SAV introduction on traffic noise implementing a Munich traffic simulation on MATSim. For the simulation they build upon the DRT module of MATSim and implement a service area that covers almost the entirety of the city [147]. Additionally, the introduction of SAVs has been realized in two versions, either by replacing car plans of all agents by SAV travel (trips that can not be served due to the service area have been cut out) or by providing freedom of travel mode choice [147]. Depending on the ride-pooling system, key findings show that stop-based pooling significantly reduces noise, while door-to-door pooling might increase noise due to extra detours [147]. Consequently, the definition of modeling components can lead to notable variations in outcomes and highlights the complexity of traffic analyses and in turn, emphasizes the importance of using frameworks like MATSim that are able to depict high complexity to obtain relevant results [94]. Although providing the option of free mode choice as an alternative, the study is limited in the heterogeneity of SAV scenarios as the only other SAV scenario is based on the idea of 100% SAV adoption.

Bischoff and Maciejewski [20] have conducted a SAV analysis for the Berlin City using MATSim and its DRT module. While commuting traffic has been incorporated, the SAV fleet handles traffic within the city area exclusively while this has been realized in the simulation by replacing all private car-based travel plans [20]. Consequently, a service area of exclusive use for SAVs has been introduced. Additionally, Bischoff and Maciejewski [20] conducted analysis of two variations of that scenario: assessing a smaller service areas with mobility hubs, in which SAVs return to when idle, and assessing the impact of replacing all public transport by SAVs. They conclude that a reduced service area results in an increased system efficiency while the replacement of public transport by SAVs leads to a required increase of fleet size from 11,000 to 12,000 accounting for a total of 323,000 vehicles trips in Berlin [20]. Moreover, the scenario of SAVs covering all of the Berlin's car-based traffic resulted in the requirement of 100,000 SAVs [20]. Consequently, this analysis showcases how regulatory intervention can be applied to replace car-based traffic in Berlin while focusing on an assessment of the number of vehicles required to serve this demand. Lastly, Bischoff and Maciejewski [20] suggest that when SAVs are being introduced, the population of Berlin might have already experienced some growth, potentially influencing simulation results, however, did excluded a forecast from their scope.

In conclusion, few theoretic simulations and generic simulation approaches do not appropriately allow to derive realistic SAV simulations [39]. Moreover, we derive potential to improve on the currently limited implementation of heterogeneous scales of SAV adoption in the agent-based simulations. For comparison, Zwick et al. [147], and Bischoff and Maciejewski [20] incorporate two scales of regulatory interventions. In turn, both studies show a promising approach of incorporating regulatory interventions to model SAV introduction scenarios.

3.3 Sustainability of AV and SAV Traffic

Various categories of research can be recognized for determining the sustainability implications of SAV traffic in the current research body. First, literature reviews summarize results of various studies to determine environmental impacts of AVs and SAVs [5, 6, 88, 119, 134]. Secondly, alternative (non-simulation-related) empirical studies such as surveys [3, 9, 38] and case studies [41, 53, 108]. Lastly, simulations (predominantly agent-based) [32, 36, 45, 115, 126] describe another fundamental research methodology in order to analyze sustainability impacts of AVs and SAVs. Since we focus on an agent-based simulation in our analysis, the current research body of this category is outlined in more detail. When discussing sustainability implications, we are referring to factors such as changes in emission generation, land utilization, and energy consumption.

Tu et al. [126] analyzed the near-road greenhouse gas emissions, NO_2 concentration and energy consumption using an agent-based simulation on MATLAB to introduce electric CAV traffic in the area of downtown Toronto. The study found that increased CAV shares notably reduced greenhouse gas emissions due to less congestion and stop-and-go conditions, particularly in heavy traffic situations [126]. In turn, energy savings have not been significant with CAV introduction, energy savings in dense traffic from reduced speeds and regenerative braking can not offset the higher energy use due to extended clearance times [126]. A core limitation of this study describes that emission generation and energy consumption related to the production of vehicles have not been considered.

Harper et al. [64] estimated energy use, emitted emissions and required parking with the introduction of AVs based on a agent-based model implemented in Python. They estimate emissions and energy use based on the total vehicle kilometer as a core output of their simulation. Based on the assumption that AVs, after dropping off passengers, have the ability to search for cheaper parking lots, the overall parking demand is derived dynamically in the simulation accounting for availability and cost of parking [64]. They conclude parking spaces, especially in the downtown area, to be freed up while the energy use and greenhouse gas emissions increase up to 3% [64]. This emphasizes the need for contrasting different perspective on sustainability while a core limitations of this work describes that only the perspective of driving-related emissions have been included.

Patella et al. [115] compared the life cycle impact of AVs on a hypothetical 100% electric AV scenario using a traffic simulation-based approach to model traffic in the city of Rome. They further compare a 100% electric AV scenario with a 100% electric non-AV scenario and concluded a reduction of the car-related environmental impact of around 60% for electric AVs and around 62% for electric non AVs [115]. Consequently, not only the impact of AV introduction but also the impact of fully electric AVs are being contrasted to analyze sustainability impacts without automation. While the approach of considering the complete life cycle is very promising, the study lacks the implementation of heterogeneous AV scale adoption rates by only focusing on the 100% AV scenario.

Martinez and Viegas [104] studied the impact of introducing SAVs in Lisbon in 2010/2011. Removing private cars, they considered scenarios with SAVs alone and combined with automated shuttle buses. In the combined scenario, their findings show 28.7% of total trips were by SAVs and 29.2% by taxi buses. Private car travel was replaced by 46.7% SAVs and 36.1% buses. They conclude a potential reduction in CO_2 emissions of 38.2% for the combined scenario and 32.4% for the SAV only scenario [104]. While only considering tail-pipe emission the studies lacks a comprehensive sustainability impact analysis.

Bridgelall and Stubbing [24] analyzed the effect of CAVs on land use. They conclude, the introduction of CAVs could increase land demand twofold or even threefold as population growth might increase the demand for land use for shopping, entertainment, or dining by almost 60% [24]. This increase of travel-related land demand is linked, for example, to the increased accessibility of CAVs to the non-driver population [24]. Hence, it emphasizes the significance of incorporating various sustainability factors, as they may present contrasting implications associated with the introduction of AVs.

To sum up, a general issue describes the fact that a majority of articles focus on energy consumption and traffic-related emissions as core sustainability measurements. Additionally, the need for more research on sustainability effects of various SAV scales and a more holistic sustainability analysis can be identified [119].

4 Method

In Chapter 3 we identify research gaps and approaches to improve upon. In the following we initially outline how these are linked to our methodology.

Travel demand-related research gaps. We observe limited realism of current agent-based AV simulations being based on outdated travel data [68]. Therefore, we incorporate a travel demand forecast based on population growth and age-related travel demand, acknowledging the non-imminent implementation of SAVs [47, 20]. Additionally, AV and SAV adoption is based on yet unclear dynamics. Policy regulations are assumed to be a solution to steer SAV adoption [13]. We introduce three scales of mandatory SAV zones in our simulation as regulatory interventions. Recognizing uncertainties in demand forecasts, we consider a range of scenarios. Thus, our analysis includes three travel demand scales: unchanged, small growth, and high increase.

Simulation-related research gaps. We mainly conclude potentials to improve upon to be the currently limited implementation of heterogeneous scales of SAV adoption in agent-based simulations. Our regulatory interventions of our approach address three scales of SAV adoption. Additionally, we identify some studies to build upon a theoretic population and a generic simulation approach, not appropriately allowing to derive realistic SAV simulations. In our study, we draw upon a calibrated agent-based simulation model, the Open Berlin Scenario [146], allowing for a more natural representation of travel demand and analysis of real-world problems [15].

Sustainability analyses-related research gaps. We identify the need for more research on sustainability effects of various SAV scales and a more comprehensive sustainability analysis [119]. We address these research gaps through a scenario based MATSim simulation of various traffic types as well as SAV adoption scales and a comprehensive sustainability analysis based on the traffic related emissions, the expected life-cycle greenhouse gas impact and the total energy consumption.

Next, we outline our methodology in more detail. After a general description of our simulation approach in Section 4.1, we deep-dive into the method of demand-forecasting in Section 4.2 and the derivation of our simulation scenarios in Section 4.3. Following that we summarize the method for our sustainability impact analyses in Section 4.4.

By outlining our approach of setting up the agent-based SAV simulation and necessary adjustments to existing solutions, we initially tackle the second research question before concluding it in Chapter 5. However, detailed descriptions of the adjustments made to the Open Berlin Scenario and data sets to derive the intended scenarios are not included here. Instead, these adjustments are thoroughly documented in Chapter 5.

4.1 General Approach

As outlined in Chapter 3 MATSim describes the most adopted framework for AV simulations [94, 83]. This is due to its capabilities of simulating complex networks or numerous agents combined with a co-evolutionary optimization (agents optimize e.g., travel plans individually), making it ideal for AV analyses [94]. In turn, MATSim shows high computation power demand and is commonly used for 1% to 10% of a regions traffic [94]. As the down-scaled 10% versions offers valuable insights without significant side effects [20], we build our general approach of the agent-based simulation on MATSim. In Chapter 2 we introduced that multiple MATSim scenario models exist (for different cities and metropolitan areas). In our study, we build on MATSim's Open Berlin Scenario (Step 1 in Figure 4.1). We chose the Open Berlin Scenario as it describes a well calibrated model [146] enabling us to realistically analyze impacts of SAV introduction. Moreover, many researchers have previously implemented the simulation model (e.g., [21, 84, 92, 145]), leading to improved comparability of our results.

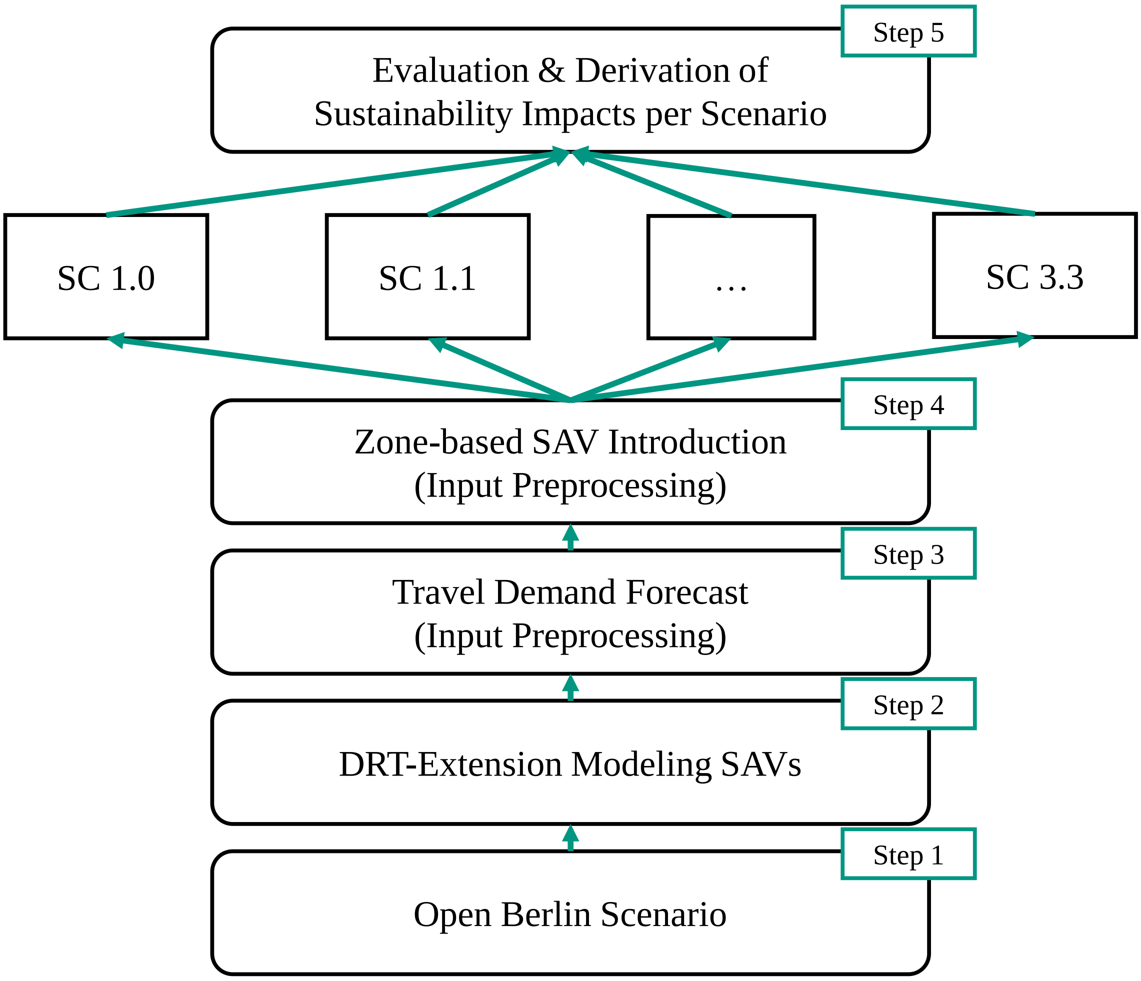


Figure 4.1: Approach of our agent-based simulation to derive sustainability impacts.

Additionally, we employ the DRT module, as detailed in Chapter 2.3, to integrate a SAV fleet

(Step 2 in Figure 4.1). The DRT module has been employed in numerous studies to simulate SAVs [84, 92, 95, 102, 130], providing increased comparability of our analyses. Additionally, the module is particularly suitable for SAVs since it allows vehicles to be dispatched in real-time within the simulation [94]. Next, we project travel demand by considering factors such as population growth and age-dependent travel behavior, as outlined in detail Chapter 4.2 (Step 3 in Figure 4.1). Based on our forecast we adapt inputs of the simulations accordingly. Next, we incorporate SAV adoption by introducing our three stages of SAV zones that prohibit car-based traffic, with the exception of SAVs (see Step 4 in Figure 4.1). A more detailed description of the SAV zones and the subsequent scenario derivation is outlined in Section 4.3. Finally, we evaluate our results and derive sustainability implications for each scenario based on changes in travel demand and our regulatory interventions (Step 5 in Figure 4.1). A comprehensive explanation of the methodology employed to derive sustainability impacts can be found in Chapter 4.4.

4.2 Travel Demand Forecast

In the following, we provide a more exhaustive outline of our forecasting approach, explaining how we set up the forecast of the overall travel demand and how we incorporate changes of the overall travel demand into the MATSim simulation.

Set up of the scenario forecast. For our travel demand forecast of 2050 we incorporate the factors population growth, age compositions and age-related travel demand, see Figure 4.2).

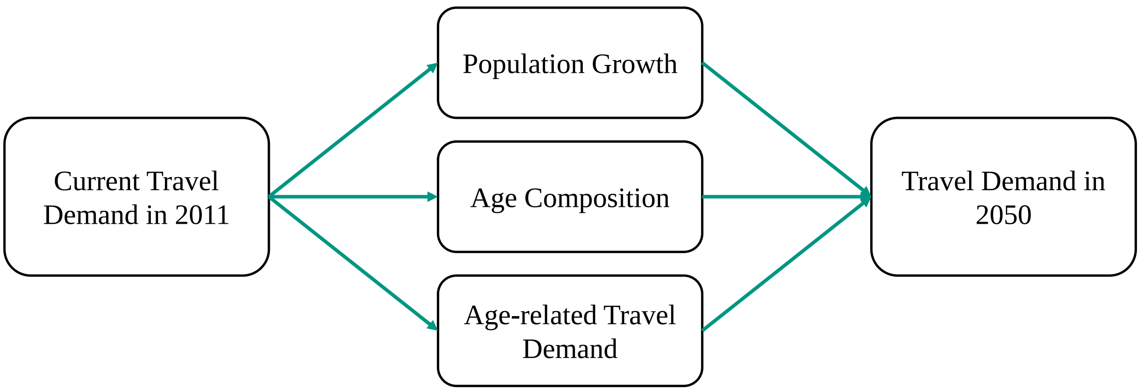


Figure 4.2: Approach and key inputs for the travel demand forecast until 2050.

We build upon Cokyasar et al. [36] that incorporated basic population growth, vehicle type changes, and technology improvement as well as Hidaka and Shiga [68] that considered factors such as age compositions and age-related individual travel needs (see Chapter 3). Influences coming from vehicle type change and technology improvements have not been considered due to the high uncertainty of their impacts. While optimistic behavior adoption indicates increased travel demand with new user groups using AVs [115], behavioral barriers might suggest minimal adoption of new technologies [71]. Aside from this, impacts of the availability of SAVs are directly incorporated in our simulations that include SAVs. Using predictive models from the German Institute for Statistics (Destatis), we formulate three primary population growth scenarios. The data set, detailing the 2011 population baseline is derived from the Zensus survey [123], in alignment with the Open Berlin Scenario [146]. While future population sizes per age-group are derived from Genesis [123]. Both being statistical resources of Destatis. These scenarios consider varying growth rates per age group. Recognizing varying travel demands for each age group, we've introduced an age factor to represent average daily travel patterns. Travel demand per age group is based on a German mobility report by infas ("Institut für angewandte Sozialwissenschaft") and DLR ("Deutsches Zentrum für Luft- und Raumfahrt") [76]. This method ensures accurate representation of factors like an aging population in our analysis, noting that older individuals typically travel less than the working-age population [76].

Incorporating the forecast into MATSim. As outlined in Chapter 3, Cokyasar et al. [36] assumed a direct relation between population growth and number of trips in their simulation. Given that MATSim utilizes plans of each distinct agent as input for travel demand, we accordingly incorporate our changes in traffic into these plans. More precisely: With a total travel demand increase (e.g., assuming a 5% increase), inclusive of the age group factor, we proportionally increase the total number of agents and plans (e.g., resulting in a 5% increase of total travel plans). The underlying hypothesis is that an increase in travel demand correlates directly with a proportional increment in the quantity of agents and travel plans. The approach of introducing travel factors based on age group is necessary as we do not have detailed information of the age group per agent in MATSim, otherwise, we could directly introduce the population growth per age group in the input files. To add greater complexity into the demand forecast, an alternative describes establishing the Open Berlin Scenario from scratch. This would include reproducing all its steps from introducing a future population to the derivation of the final travel plans for each forecast scenario. However, this implementation falls beyond the scope of our analysis.

4.3 SAV Zone and Scenario Derivation

Building upon Bischoff and Maciejewski [20] and Zwick et al. [147] which suggested regulatory measures for SAV-only car travel and an alternative scenario, we introduce three SAV zones: Berlin's city center, the whole city, and the combined area of Brandenburg and Berlin. Using these zones and our travel forecast, we derive twelve scenarios for our final simulation analysis.

Table 4.1 provides a comprehensive overview of our scenarios. The first numbers in the scenario designation represent the forecasting scale whereas the second number represent the scale of SAV introduction.

Scenario 1.0 (SC1.0) represents an unchanged travel demand scenario (2011-Baseline) and no SAV introduction. It utilizes population data from 2011 [122] and commuter statistics from 2009 [29] as in the Open Berlin Scenario. Scenario 2.0 (SC2.0) and scenario 3.0 (SC3.0) account for increased travel demand by incorporating a low (2050-Low) and high (2050-High) travel demand forecast while no SAVs are introduced either. The travel demand changes are derived from population growth dynamics according to Destatis [123] and daily travel patterns provided by infas and DLR [76]. Our 2050-Low growth forecast is based on Destatis' G2L2W2 and the 2050-High forecast on Destatis' G2L2W3 population growth scenario. Both have similar birth and life ex-

Nr.	Travel Demand Scenario	SAV Scenario	Abbreviation
1.0	2011-Baseline	No SAVs	SC1.0
1.1	2011-Baseline	City center ban	SC1.1
1.2	2011-Baseline	City wide ban	SC1.2
1.3	2011-Baseline	Simulation wide ban	SC1.3
2.0	2050-Low	No SAVs	SC2.0
2.1	2050-Low	City center ban	SC2.1
2.2	2050-Low	City wide ban	SC2.2
2.3	2050-Low	Simulation wide ban	SC2.3
3.0	2050-High	No SAVs	SC3.0
3.1	2050-High	City center ban	SC3.1
3.2	2050-High	City wide ban	SC3.2
3.3	2050-High	Simulation wide ban	SC3.3

Table 4.1: Overview of the twelve core scenarios of our analysis.

pectancy rates but differ in immigration-emigration ratios. The G2L2W2 growth scenarios has been chosen as it combined with our unchanged 2011-baseline maps a wide range of population growth scenarios by Destatis [123]. G2L2W3 averages the travel demand between the two.

Scenario 1.1 (SC1.1), scenario 2.1 (SC2.1) and scenario 3.1 (SC3.1) focus on the Berlin city center, mandating SAVs and restricting other cars. Other modes, such as walking and cycling remain allowed. This targets the densest car travel area, as advantages for introducing a shared fleet are assumed to be most effective. Scenario 1.2 (SC1.2), scenario 2.2 (SC2.2) and scenario 3.2 (SC3.2) expand the SAV zone to all of Berlin. Thereby, we analyze the impact on the majority of car travel, excluding inter-rural traffic. Lastly, scenario 1.3 (SC1.3), scenario 2.3 (SC2.3) and scenario 3.3 (SC3.3) represent the broadest case, replacing all car travel with SAVs in Berlin and Brandenburg.

4.4 Sustainability of SAV Traffic

From our scenario analyses, we are using the outputs to assess the sustainability impact of each scenario. Based on the total vehicle kilometer, three indicators are being calculated as described in Table 4.2. The combination of all three is intended to provide a more in-depth understanding of the sustainability impact of SAV introduction. Enhancing this, supplementary analyses are undertaken to examine impacts of variations in fleet size, and the selection of central parking hubs for the SAVs.

Prior to any calculations, we outline our underlying assumptions and considered factors regarding the derivation of energy consumption and emission generation.

Factors of energy consumption. Within the domain of transportation research, numerous factors are considered to determine energy consumption. These can be classified into weather, roadway, vehicle, travel, traffic and driver related variables [143]. We exclude weather and roadway factors from our analysis as non-observable given our MATSim-based simulation approach. In turn, we incorporate vehicle-related factors by differentiating energy consumption per powertrain

Nr.	Sustainability Indicator	Description
1	Total energy consumption	The total energy consumption as a combination of electricity and gas demand.
2	Greenhouse gas of mobility system	The traffic-based greenhouse gas emissions of all cars and SAVs.
3	Expected life-cycle greenhouse gas	Production, traffic, and disposal-related greenhouse gas emissions of all cars and SAVs (similar to Patella et al. [115]).

Table 4.2: Overview of the indicators utilized to derive sustainability impacts.

while distinguishing two main powertrain adoption scenarios. This includes one scenario of an unchanged powertrain split and a 100% BEV scenario to contrast to possible extremes while enabling us to derive SAV-related sustainability impacts independent of future powertrain developments. Secondly, we incorporate travel-related energy consumption explicitly per powertrain type. In a similar manner, Patella et al. [115] distinguished energy consumption based on powertrain type. Lastly, we consider driver- and traffic-related characteristics implicitly by accounting for AV-related efficiency increases with the introduction of SAVs. We build upon Gawron et al. [52] that concluded AV related efficiency increases associated with e.g., platooning and eco-driving.

Factors of emission generation. Likewise, the derivation of car-related emissions is regarded as a complex problem. Scholars such as Weilemann et al.[133] or André and Rapone [11] for instance, undertake the distinction between emissions during cold-start and warm periods, being influenced by factors such as vehicle type, driving behavior (e.g., driving velocity and accelerating speed), and ambient temperature [146]. Again non observable factors like the ambient temperature have not been included in our approach. Instead, we focus on deriving the emission generation based on vehicle type by accounting for various powertrains and two powertrain adoption scenarios. Additionally, we incorporate general driving related emissions and AV-related efficiency improvements to implicitly account for driving behavior changes. Similarly, Harper et al. [64] and Fagnant et al. [45] derived total of energy consumption and emissions generation based on induced vehicle kilometers. To ensure the sustainability impact analysis to be more holistic, we additionally include the emissions generated in the process of vehicle production. We draw upon the approach of Patella et al. [115] and Gawron et al. [52] and account for non driving-related emissions caused by end of life, maintenance and construction processes in our analyses.

5 Experiments

In the following, we describe how our simulation approach is realized through scenario experiments. We provide a guideline for the data preprocessing and settings to reproduce the scenario results in Section 5.1. Additionally, we explain the supplementary analyses undertaken to observe factors such as the impact of fleet size and the introduction of central SAV hubs in Section 5.2. Lastly, we provide an overview of MATSim output files from which we derive our simulation results in Section 5.3. With that, we answer our first and second research question conclusively:

- What approaches and inputs for the scenario models of SAV simulations can be derived from literature?

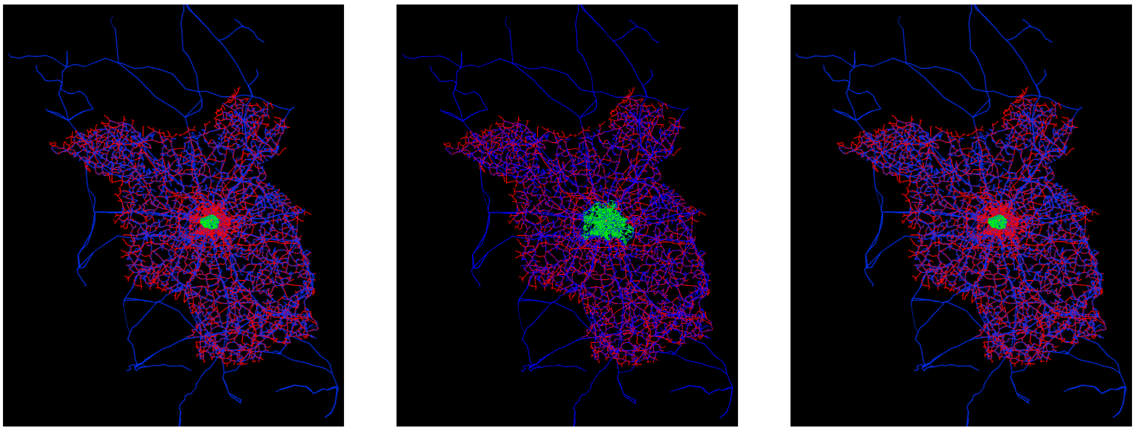
- How can various scales of SAV introduction in the private passenger transport sector be realized using an agent-based simulation?

5.1 Data Preprocessing and Scenario Set Up

Each scenario necessitates variations in the data preprocessing, which we will now elaborate upon, aiming to enable effective replication and comprehension of our outcomes. Therefore, five input files are being referred to in the following. Each file is described in Table 5.1.

Nr.	Input File Name	File Type	Description
1	Plans	xml	Includes the population of agents and their daily travel behavior represented as travel plans per person. Next to time of travel, starting point and destination, the traffic mode is determined in the plans file.
2	Network	xml	Entails all streets and connections (represented by nodes and links) of Berlin and Brandenburg as well as the traffic mode that allows to travel the links.
3	SAV operation	shp	This file contains the network area in which SAVs are allowed to travel. It initially used as an input to update the network file introducing SAV traffic.
4	Car vehicle	xml	Includes the number of cars that are being operated with an according vehicle id and length.
5	SAV vehicle	xml	Includes the number of SAVs that being operated and additional vehicle characteristics such as length and amount of passengers.

Table 5.1: Overview of the required input data sets for preprocessing.



(a) Berlin city centre. (b) Berlin city. (c) Berlin and Brandenburg.

Figure 5.1: Visualisation of the three scales of non-SAV ban areas using Simunto [120].

Data preprocessing for SC1.0, SC2.0 and SC3.0. Following the methodology delineated in Section 4.2, we integrate the forecast for travel demand. This increase in travel demand is subsequently realized within the MATSim simulation, accomplished by the duplication of agents within the population, in proportion to our forecasted travel demand increase.

Furthermore, the travel timestamps are randomly assigned from a list of all car-related departure times to ensure that the derivation of departure times is not skewed. In case duplicated plans involve travel by car, an additional entry is set to the file of vehicles to ensures the successful execution of the associated travel plan. All Python scripts that execute preprocessing are accessible in our Git repository under the section of data preparation as well.

Data preprocessing for SC1.1, SC2.1 and SC3.1. The execution of the non-SAV ban within Berlin's city center necessitates modifications to the following files: the travel plans of agents, the network of streets, the operational network for SAVs, and SAV vehicles. Starting with the travel plans, all links originally designed to navigate through the non-SAV ban area via car are replaced with SAV travel as the only car-based travel mode. The network file, which includes links and their associated traffic modes, is further enhanced to facilitate SAV travel along all routes previously accessible to cars. This modification guarantees that SAVs have unrestricted access across Brandenburg and Berlin and are not solely confined to the SAV ban zone. Next, all non SAV car-based travel will be excluded from links within the city centre of Berlin as depicted. The resulting links can be seen in Figure 5.1. The depicted lines correspond to the streets of Berlin and Brandenburg. The red-marked roads signify car-based travel (private cars and SAVs), green-marked roads are designated for SAV travel only (excluding private, non autonomous cars) and blue-marked roads represent public transport routes.

Finally, the number of SAVs in operation within Berlin is set to 100,000 units for all scenarios while the simulation itself optimizes the fleet size by only activating necessary units. The 100,000 units well above the number of activated SAVs across all scenario, is intended to enable the MATSim simulation to find ideal flee sizes. Alternative fleet sizes are being tested as stated in Section 5.2. Lastly, variations to the individual SAV settings, such as cost of usage, vehicle length and passenger seats, are kept at the standard values across all scenarios.

Data preprocessing for SC1.2, SC2.2 and SC3.2. Similarly, the implementation of the non-SAV ban across the entirety of Berlin is facilitated through adjustments to the agents' travel plans, the basic network for all traffic modes, the operational network for SAVs, and SAV vehicles. The primary distinction to Scenario X.1 lies in the wider expansion of the non-SAV ban area in the network file as depicted in Figure 5.1a and the according replacement of car-based travel plans and travel links by SAVs in the plans file. As a result, a higher share of actively used vehicles is required to sufficiently accommodate increased demand and coverage.

Data preprocessing for SC1.3, SC2.3 and SC3.3. Finally, the non-SAV ban implementation across all of Brandenburg and Berlin is realized via similar modifications to the travel plans of agents, the primary network for all transportation modes, the operational network for SAVs, and SAV vehicles. The non-SAV ban now encompasses the complete simulation area as seen in Figure 5.1c.

5.2 Additional Analyses of Scenario Modifications

To further test factors related to SAV introduction and their sustainability impacts, we conduct additional examinations. We aim to isolate SAV-specific implications independent of our forecast implementation, while testing our 100% SAV introduction as the extreme of our SAV introduction alternatives.

Impacts of a changed fleet size. Recognizing that the number of SAVs represents a significant lever for promoting sustainable traffic, we perform a separate analysis to assess the impacts of diminishing the fleet size. The analyzed fleet sizes amount to 20%, 40% and 60% of the by MATSim activated number of SAVs. We intend to test whether a reduced total vehicle distance traveled and therefore, reduced energy consumption and driving-related emissions can be achieved.

Impacts of changed vehicle size. Next, we conducted an analysis to understand the consequences of varying vehicle sizes, specifically comparing four-seat SAVs to six-seat variants (similar to [28, 104]). As a assumption for all other scenarios, we have employed the four-seat SAV configuration as it describes a widely-established setting amongst scholars (e.g., [48, 67, 93, 100, 130]).

Impacts of mandatory SAV hubs for idle vehicles. The positioning of SAVs holds a pivotal role in influencing the total travel distance and duration. In this context, we undertake a comparative evaluation of two distinct allocation strategies and potential sustainability implications. The first strategy, used in our scenarios, assumes that the most promising location for starting each day of driving is the last destination of the SAV from the preceding day. Thereby, the vehicle remains in close proximity. Additionally, idle vehicles stay at the same location. The second approach, assumes that vehicles consistently return to a designated central depot (e.g., a SAV hub) when idle or at the conclusion of each day, where they are for instance parked, refueled, recharged or maintained.

5.3 Data Postprocessing and Output Files

Every simulation run generates a set of output files in MATSim. Below, we detail the output files used for our analyses. These files form the baseline of our analyses, with further details provided in Table 5.2. Most output files offer data that we directly incorporate, such as the passenger kilometers and hours traveled from the pkm and ph modestats files. However, more detailed analyses require postprocessing, such as traffic density being extracted out of the output events file. The specific adjustments are being indicated accordingly in Chapter 6.1.

Nr.	Output File Name	File Type	Description
1	Output persons	csv	Contains data points such as id, locations, last activity links, based on which population density analyses can be derived.
2	Pkm modestats	txt	Contains the traveled distance per travel mode and is used without postprocessing.
3	Ph modestats	txt	Includes the traveled hours per travel mode and is used without postprocessing.
4	Occupancy time profiles	txt	Contains an overview of occupied vehicles per occupancy level and time stamp and is used without postprocessing.
5	Detailed distance stats	csv	Documents the SAV km traveled per occupancy level and is used without postprocessing.
6	Vehicle stats	csv	Documents the total distance and empty distance and is used without postprocessing.
7	Vehicle distance stats	csv	Documents the individual distances traveled per SAV which can be used to derive the number of active vehicles and travel statistics.
8	Output events	csv	Contains all events, e.g. an agent requesting a ride and vehicles entering or leaving a link. It can be used to analyze heavy traffic and .
9	Wait stats	csv	Documents the statistical figures around SAV waiting times such as the average, median and 95 percentile of waiting times.
10	Leg histogram	txt	Contains all departures, arrivals and in traffic events per travel mode and is postprocessed to derive aggregate numbers.
11	Output events	xml	Documents all events, e.g. an agent requesting a ride and vehicles entering or leaving a link. It can be used to extract e.g. analyses of heavy traffic per link.
12	Trips	csv	Contains all trips per agent, figures such as average distance and duration can be derived.

Table 5.2: Overview of the required input data sets for preprocessing.

6 Results and Evaluation

In the following, the results of the travel demand forecast, the simulation of SAV scenarios and their sustainability implications are being outlined in Section 6.1. To better assess these results an evaluation and comparison to related work is being conducted in the Section 6.2.

6.1 Key Results

By laying out our core results, we address our third and final research question:

- How can the different SAV scenarios be evaluated and how do they perform in direct comparison, particularly in regards to sustainability impacts?

6.1.1 Travel Demand Forecast

As outlined in Chapter 4, we initially formulate three distinct scenarios for travel demand developments. The first scenario assumes a stable population size. The third anticipates a significant population increase, while the second scenario represents a moderate alternative, close to the average, of the two. In the following, we derive the travel demand changes based on population growth for the high travel demand scenario 3, see Table 6.1. As outlined in Chapter 4, the numbers of current and future population sizes are derived from Destatis databases [122, 123]. The calculations for the moderate travel demand scenario 2 can be found in the Appendix in Section 8.2.

Age Group	2011 [122]	2030 [123]	2050 [123]	Change 2011-2050	Age Factor	Population Share	Overall Travel Impact 2011-2050
18-19	87	133	138	57.8%	0.74	1.8%	0.7%
20-29	756	744	801	6.0%	1.18	15.4%	0.9%
30-39	731	897	931	27.4%	1.28	14.9%	4.5%
40-49	966	1,016	926	-4.1%	1.31	19.6%	-0.9%
50-59	859	770	926	7.7%	1.28	17.5%	1.5%
60-69	660	877	934	41.7%	0.92	13.4%	4.4%
70-79	595	646	612	2.8%	0.64	12.1%	0.2%
80+	262	340	501	90.9%	0.36	5.3%	1.5%
Total	4,916	5,423	5,770	17.4%	-	100.0%	14.9%

Table 6.1: Travel demand derivation assuming high population growth across Berlin and Brandenburg.

We initially differentiate population growth per age-group in Table 6.1. We conclude a total population growth of 21.3% when comparing the totals of 2011 to 2050 with a growth per age group varying from -4.1% (age group 40-49) to 90.9% (age group 80 and above). However, as shown in Figure 6.1 variations in daily travel behavior among different age groups exist. We can identify an increasingly diminishing influence of population growth among age groups above 69 and below 19, whereas population growth within the 29 to 59 age bracket results in an even more pronounced impact on travel demand.

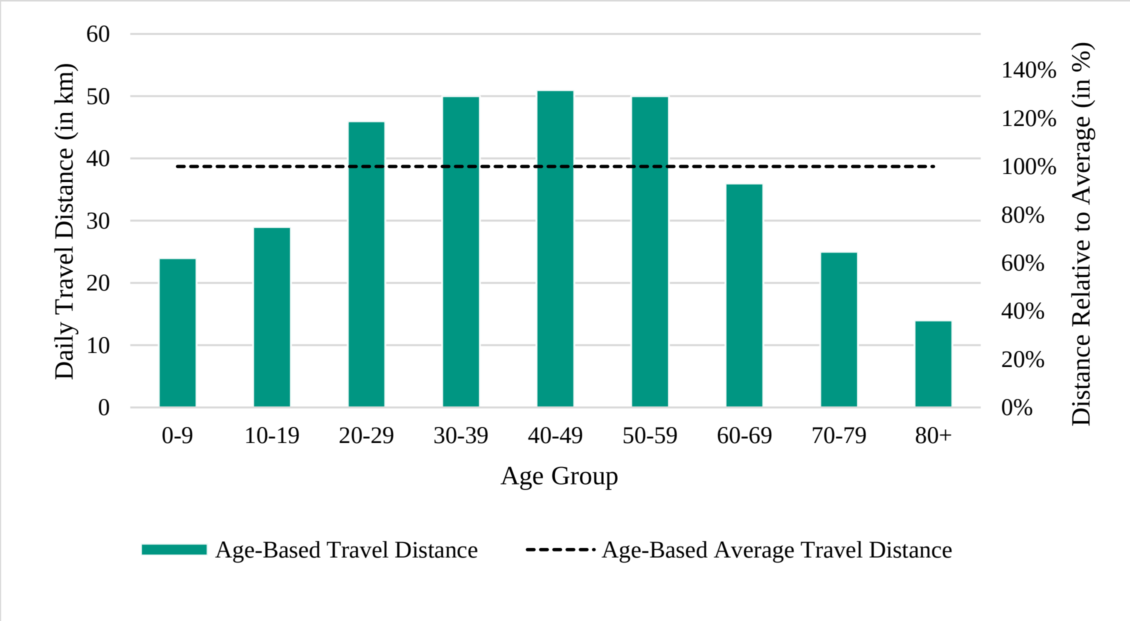


Figure 6.1: Age-based Travel demand in Germany as of 2017 adapted from Infas and DLR [76].

Consequently, we include an age factor of travel demand that accounts for the impact of the travel demand per age group in relation to the average travel demand of all age groups. As described in Chapter 4, the approach is necessary as we can not apply growth per age groups in MATSim directly, not knowing the age per agent. In turn, we derive the average travel demand across all age-groups with our population projection before implementing it through agent-duplication into MATSim. To derive the travel demand factor we apply Equation 6.1.

$$f_a = \frac{t_a}{\bar{t}} \qquad [6.1]$$

where:
f_a = Age-based travel demand factor per age group a
t_a = Age-based travel demand per age group a in daily km
$\bar{t}$ = Average age-based travel demand across the total population in daily km
Based on the age-factor, our population growth and the share of total population per age group, we derive our impact on the overall travel demand per age group using Equation 6.2.

$$T_a = p_a \times f_a \times s_a \qquad [6.2]$$

where:
T_a = Overall travel impact per age-group a in %

p_a = Population growth per age-group a in %

f_a = Age-based travel demand factor per age group a

s_a = Share of total population (aged 18 and above) per age-group a in %

For the calculation of the population share, we included the population aged 18 and above inline with the agent population of the Open Berlin Scenario. Figure 6.2 shows the result of a reduced travel demand increase compared to population growth in both scenario.

More precisely, an initial population growth of 17.4% results in a 14.9% increase in travel demand in the scenario of a high increase. One core driver for this is the age group 40-49, which represents the largest share of the population. However, this group is experiencing a population decrease, while exhibiting the highest age-based travel factor. When having a look at the resulting population and travel demand growth rates, it becomes evident that scenario 2 experiences a period of stagnation beyond 2030, following an initial phase of growth driven by immigration. In contrast, scenario 3 depicts a consistent increase in population size until 2050, as immigration numbers remain on a higher level. For our scenario analysis, we will focus on the 2050 growth figures as we assume our SAV introduction not to be feasible before 2050, similar to other researchers assuming wide AV adoption in 2045 and beyond (e.g., [13, 90]). Additionally, enhanced fine-granularity in our scenarios would be out of scope of this study.

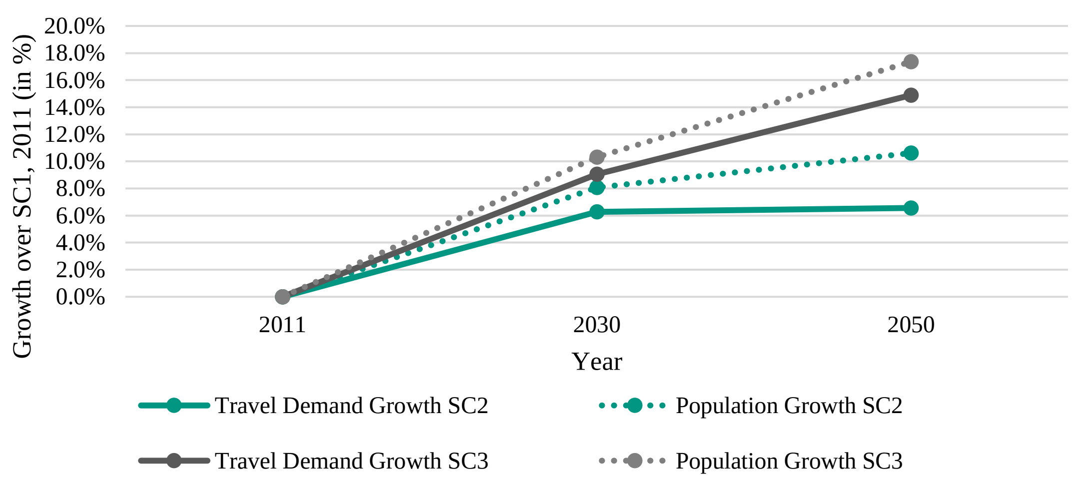
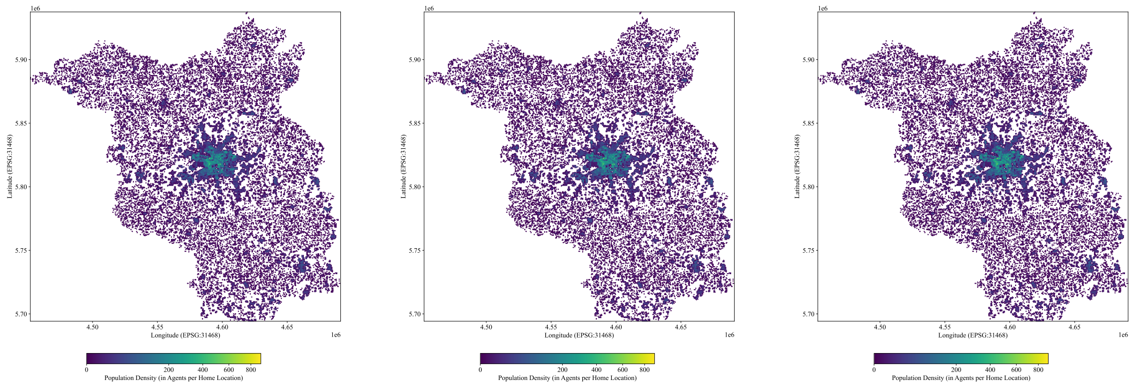


Figure 6.2: Travel demand contrasted against population growth per forecasting scenario.

Applying the travel demand increase to our simulation by duplicating agents, as described in Chapter 4, results in a total agent count of 491,351 for SC1.0-SC1.3, 523,763 for SC2.0-SC2.3 (6.6% increase) and 564,513 for SC3.0-SC3.3 (14.9% increase). The additional home locations are spread randomly across the already existing agent home locations, see Chapter 4. Consequently, the population density increases by 6.6% and 14.9%. Figure 6.3 illustrates the population density per forecast scenario, showing an increased density in proportion to previous density levels (e.g., Berlin city shows the highest absolute increase of density). The home locations of each agent can directly be extracted from the output person file, see Section 5.3.



(a) Unchanged population SC1. (b) 6.6% population growth SC2. (c) 14.9% population growth SC3.

Figure 6.3: The density of agents' home locations per travel demand scenario across Berlin and Brandenburg.

6.1.2 Scenario Results

As outlined in Chapter 2 and Chapter 5, we run our simulations using the 10% Open Berlin Scenario. A total of 491 thousand agents are represented in the baseline simulation (excluding the population aged under 18), compared to the total population of 5.7 million people in Berlin and Brandenburg [122]. 29.6% of total trips are associated with car travel, with an average car-based trip length of 9.1 kilometer, considering agents that live in Berlin [146]. An average occupation rate of 1.3 and car ownership rate of 135 thousand out of 491 thousand agents (27.6%) can be observed in the simulation. The simulations have been conducted using a 128GB RAM computer with an average computation time of 18-20 minutes (non SAV scenarios) up to 32-36 hours (100% SAV scenarios) with two simulation iterations per scenario. While our computational resources did not allow for further iterations on the 10% Open Berlin Scenario, changes in outputs beyond the second iteration can be observed in our initial testing simulation runs using the 1% Open Berlin Scenario. A test run covering 290 iterations using the 1% Open Berlin Scenario can be found in the Appendix in Section 8.3. Further settings regarding the specific scenarios set up and inputs are outlined in Chapter 5. Incorporating the projections for the year 2050 in our analysis, we now outline the outcomes derived from our twelve SAV scenarios. As all numbers are based on the 10% Open Berlin Scenario, we only include absolute numbers in graphs to better visualize changing dynamics across the scenarios. Other, we focus on a relative comparison and observable trends. Person distance or time traveled serve as a metric for assessing the simulation results in terms of the value generated for SAV agents and alterations in their individual travel duration. Vehicle kilometers, however, is the basis for our sustainability calculations, see Chapter 4. This distinction is vital as an increase in person kilometers traveled does not necessarily correspond to an increase in vehicle kilometer, particularly when shared driving describes a dominant travel mode.

Figure 6.4 shows the total passenger kilometer traveled per scenario and travel mode as a direct output of the pkm modestats file, see Section 5.3. It is observable that the total distance traveled increases, owing not only to the augmentation of travel demand across scenarios 1.0 to 3.0 but also with increased SAV-travel. When contrasting SC1.0 with SC1.3, a notable growth in total

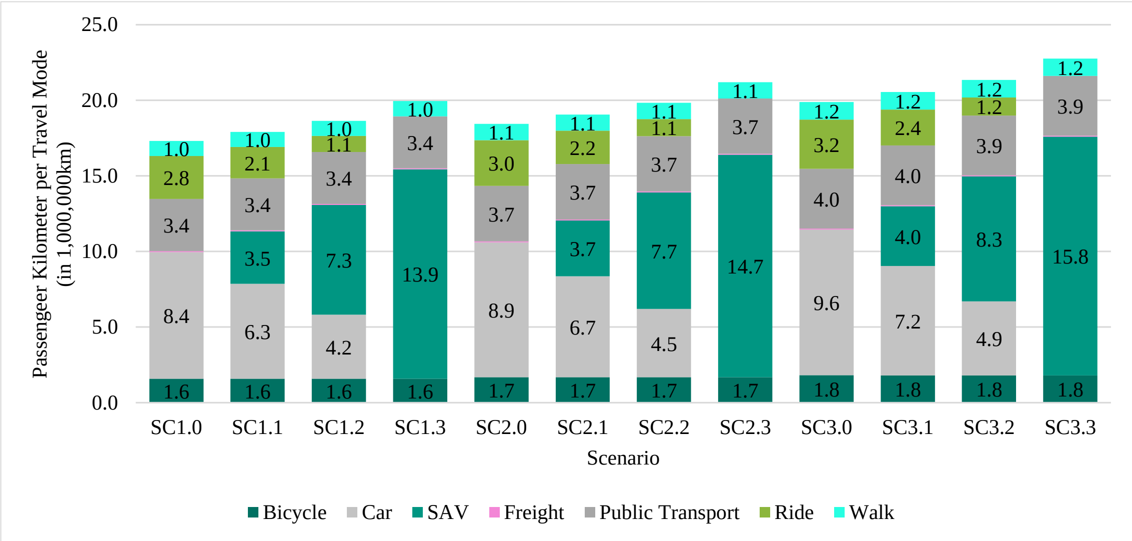


Figure 6.4: Total passenger kilometer traveled per travel mode and scenario, graphic adapted from the output files of the Open Berlin Scenario [146].

distance traveled by 15.2% becomes evident. A similar growth can be observed across SC2.0 to SC2.3 and SC3.0 to SC3.3. With an increase of 23.9% from 13.8 kilometer to 17.1 kilometer in average trip distance when comparing car-based travel (SC1.0) to fully SAV-based travel (SC1.3), SAV-travel describes a mayor driver for the increase in passenger kilometers. Average trips can be extracted from the trips file and empty distances using the vehicle stats file, see Section 5.3. We observe minimal influence on the demand for other modes of transportation, apart from the transition from conventional car-based to SAV traffic. More precisely, a proportion of travelers shifts from pedestrian and public transportation modes to SAVs. Comparing SC1.1 to SC1.3, this transition results in a reduced distance traveled by 0.4% for public transport and walking, and 0.1% for cycling. Comparing the relative mode splits in our simulation, car-based travel experiences an increase of up to 7.3% (SC3.3 over SC3.0) with the introduction of SAVs, making up 69.5% of all trips. When combining ride and car travel, a car-based share of 64.7% in trips results for the baseline scenario SC1.0.

As depicted in Figure 6.5, we can identify a similar pattern of changes in the passenger hours traveled by mode type. The figures are extracted from the ph modestats file, see Section 5.3. We can observe an even enhanced increase of passenger hours when introducing travel demand projections or SAV travel. Comparing SC3.0 with SC1.0, a 14.9% increase of travel demand leads to an increase in total passenger hours of 20.9%. Additionally, the introduction of SAVs leads to an increase of passenger hours traveled ranging from 27.5% (SC1.1 compared to SC1.0) to 62.1% (SC2.3 compared to SC2.0). Next to inefficient routing and additional passenger pick ups, Figure 6.5 shows that a mayor reason for enhanced passenger hours describes the waiting time for SAVs, referred to as SAV wait. The SAV waiting time accounts for up to 7.5% of total passenger hours (in SC3.3) while private-car travel is associated with not additional waiting times.

Similar to the comparison of absolute and relative kilometers traveled per passenger, the intro-

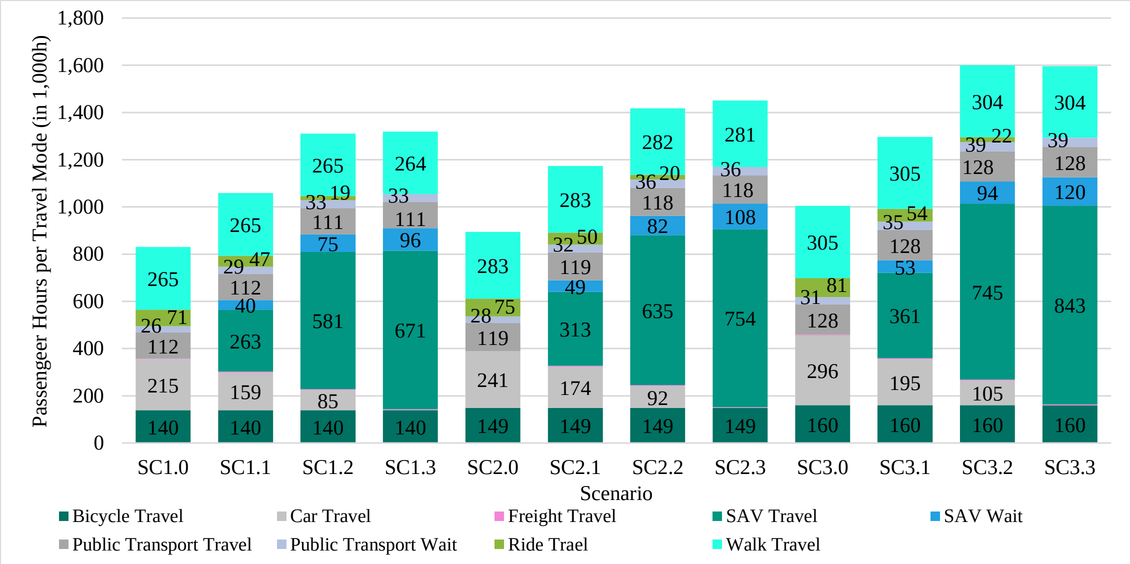
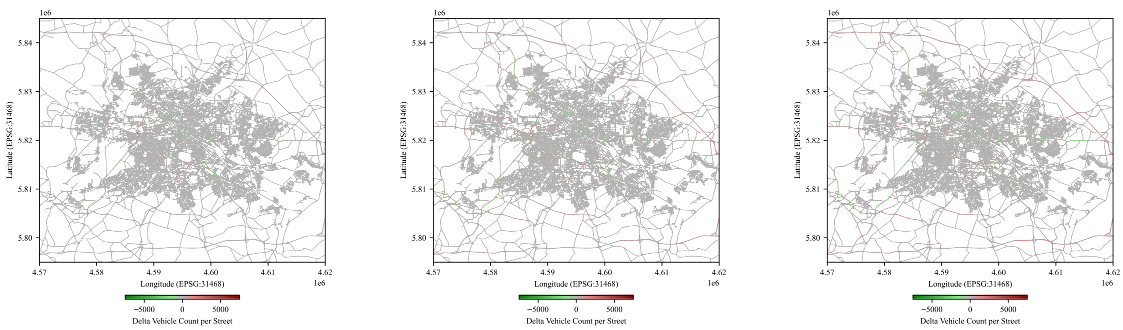


Figure 6.5: Total passenger hours per travel mode and scenario, graphic adapted from the output files of the Open Berlin Scenario [146].

duction of SAVs comes with significant changes in the distribution of time spent across different travel modes. This is enhanced by the fact that absolute numbers for bicycle, public transport, and pedestrian travel remain largely consistent. This leads to car-related travel time accounting for as much as 60.3% (SC3.3) of the total travel time, compared to 34.4% in SC1.0. When further analyzing the specific trips that SAVs take, we can identify one reason for this being an increase in the usage of main roads around the city of Berlin and West Berlin, resulting in higher traffic occurrence, see Figure 6.6. This effect overcompensates the reduction of usage of main roads inside the city center, as visible in our increase of total car-related travel. Roads marked in red indicate an increase in vehicles on those specific routes, while those marked in green indicate a decrease in vehicles. A more intense color suggests greater changes.



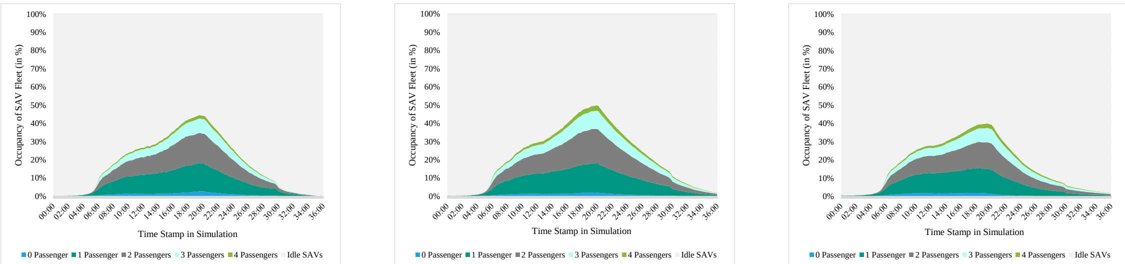
(a) Delta SC1.1 to SC1.0.

(b) Delta SC1.2 to SC1.0.

(c) Delta SC1.3 to SC1.0.

Figure 6.6: Increase of car-based travel comparing the three levels of SAV introduction to the non-SAV baseline.

We need to emphasize that a rise in passenger hours is not equal to vehicle hours traveled. With the increase of passenger occupation per vehicle, a surge in passenger hours results, related to picking up other passengers. However, vehicle hours might still be reduced due to higher occupation levels and in turn. As depicted in Figure 6.7, a significant share of actively used SAVs occupies two or more passengers, while the vehicle occupancy per time stamp can directly be extracted from the occupancy time profiles file, see the Section 5.3. We compare SC3.1, SC3.2 and SC3.3 in Figure 6.7, while similar occupancy for the other occupancy rates can be observe. For comparison, an overview contrasting scenario SC1.1, SC1.2 and SC1.3 can be found in the Appendix in Section 8.4. Using the kilometers driven per occupancy level from the detailed distance stats file, we can further calculate an average occupation of 1.60-1.67 for SC1.1-SC1.3, 1.63-1.70 for SC2.1-SC2.3 and 1.68-1.74 for SC3.1-SC3.3. Compared to the average occupation for private cars of 1.2 to 1.3 in Germany as of 2017 [76] and 1.3 in our baseline SC1.0, we conclude a comparatively small increase of occupation rate associated with SAV introduction. This is related to our high number of SAVs guaranteeing improved routing and therefore, reduced total vehicle kilometers, while not improving occupancy as a primary driver for detours. Impacts of reducing our total SAV fleet are being shown in our additional analyses in Section 6.1.5. Even though not all vehicles are simultaneously in use, the presence of a sufficient number of vehicles allows for a more rapid response to demand and therefore, acceptable service levels. As illustrated in Figure 6.7, the proportion of simultaneously occupied vehicles remains below 50% of the total fleet size of up ranging from 27.2 thousand (SC1.1) to 76.8 thousand SAVs (SC3.3). As idle vehicles in our core scenarios do not return to central hubs but rather park in a nearby location, comparatively low empty distance ratios of 1.5% to 3.1% across all scenarios result.



(a) SC3.1. (b) SC3.2. (c) SC3.3.

Figure 6.7: Vehicle occupancy of SAV fleet across the three scales of SAV introduction, graphic adapted from the output files of the Open Berlin Scenario [146].

The number of total required vehicles, cars and SAVs combined, is being reduced with an increased share of SAVs. This results in a reduction of total the vehicle fleet ranging from 11.9% (SC1.1 compared to SC1.0) to 50.7% (SC3.3 compared to SC3.0)) of the original fleet size, see Figure 6.8. We can derive an even increased impact for the scenarios that include a higher travel demand forecast until 2050, owing to the increased population density and therefore, higher ratio of shared distances traveled per agent. The numbers of total idle and used vehicles have been extracted out of the vehicle distance stats file, see Section 5.3.

The aggregate distance traveled by vehicles, encompassing all car-based traffic, is depicted in Figure 6.9. We derive these figures by extracting the car-related distances from the pkm modestats

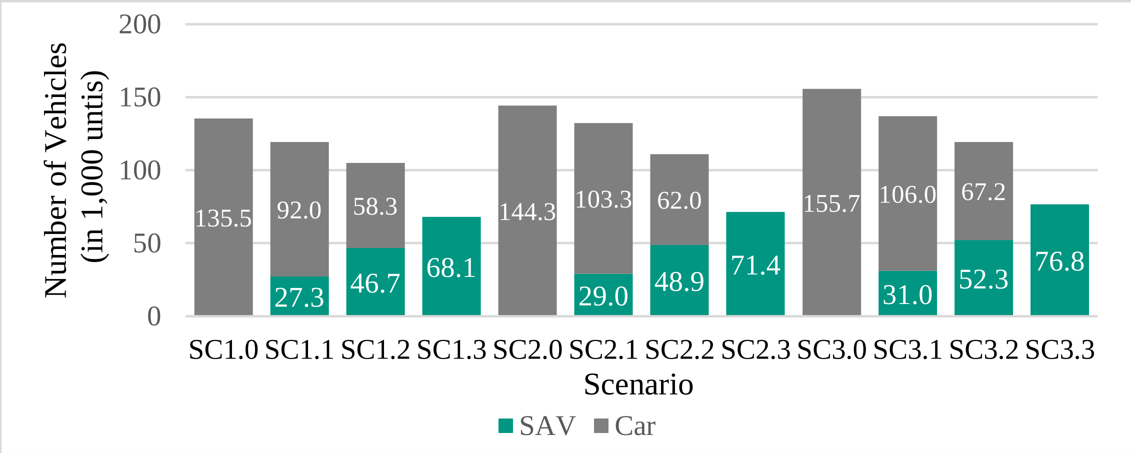


Figure 6.8: Total number of vehicles per scenario compared to each non-SAV baseline.

file and the SAV-related distances from the detailed vehicle stats file, see Section 5.3. For the scenarios not including a 100% SAV share, we assume the ride travel mode to be covered entirely by the fleet of private cars. Initially, when considering the travel demand baseline of 2011, the introduction of SAVs results in a higher total vehicle distance compared to the exclusive use of private cars. This amounts to an increase ranging from 0.8% (SC1.1) to 2.8% (SC1.2). In the scenarios including travel demand increases, we see a similar pattern compared to the three level of SAV introduction. However, the increased population density and implied traffic density improves occupancy rates, therefore, leading to a relative reduction of car-based travel. This leads to a decrease in vehicle-based kilometers of up to 1.0% for SC2.3 and 3.6% for SC3.3.

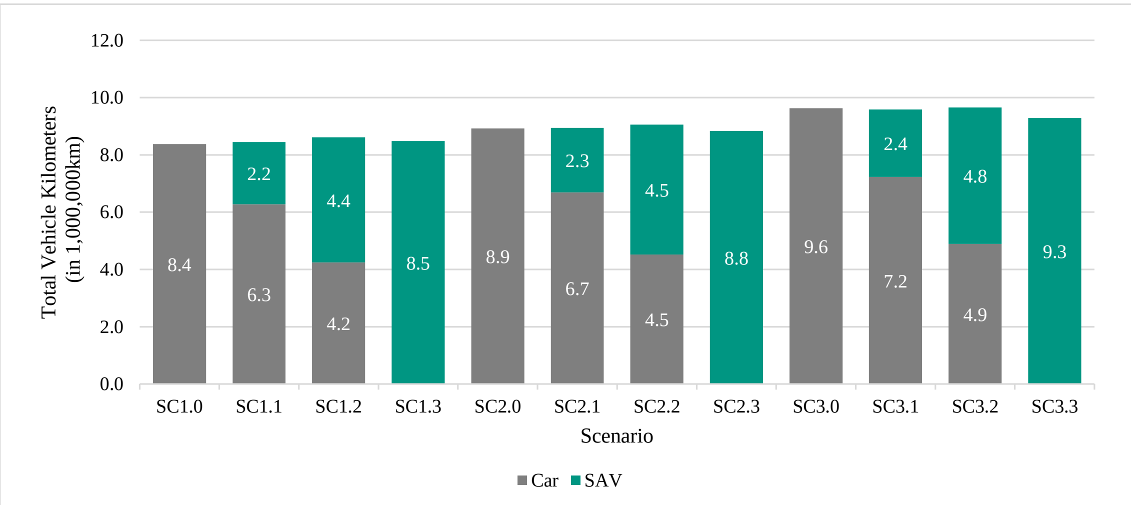


Figure 6.9: Total vehicle-based kilometer per scenario compared to each non-SAV baseline.

6.1.3 Derivation of Sustainability Impacts

Before analyzing our sustainability impacts per scenario in Section 6.1.4, we outline the calculations to derive our three sustainability indicators: driving-related energy consumption, driving-related emission generation and total life-cycle emission generation. This includes describing factors, such as the assumed powertrain-split and AV-related efficiency increases, which influence each indicator, see Chapter 4.

Powertrain assumptions. To account for possible variations in powertrain types, we distinguish two perspectives: an unchanged powertrain split and a fully electrified car fleet scenario. The comparison of both an unchanged powertrain split and the 100% BEV scenario is not intended to describe a realistic powertrain forecast. It is rather intended to provide a better understanding for impacts of SAVs on sustainability, covering a wide range of possible powertrain developments. In the unchanged scenario, we consider the combined average vehicle types by powertrain of Berlin and Brandenburg of 2011 as the Open Berlin Scenario input data is based on the same year.

- Unchanged powertrain split scenario: 78.9% gasoline, 19.7% diesel, 0.2% HEVs/BEVs and 1.2% other vehicles, mainly based on liquefied petroleum gas (LPG) in the private passenger sector [89]
- 100% BEV scenario: 100% BEVs in the private passenger sector

Driving-related emissions. The assumed numbers of emissions per kilometer and powertrain related to vehicle movement (e.g., tailpipe emissions in regards to fuel based cars) can be found in Table 6.2.

Vehicle Type	Our Baseline		Patella et al. [115]			IEA [78]	EEA/EMEP [44]
	Urban	Rural	Urban	Rural	Average	Average	Average
	in g CO_2 eq/km						
Gasoline	246.1	146.4	267.91	159.38	224.3	206	221.8
Diesel	199.4	146.4	216.96	159.03	193.7	178	190.1
LPG	185.2	157.3	231.38	196.49	217.3	-	173.9
BEV	0	0	0	0	0	70	-

Table 6.2: Emission generation per powertrain and road type.

Our baseline builds upon the average German emission generation per powertrain from the IEA [78] and LPG emissions from EEA/EMEP [44]. The IEA [78] observed data from Germany in 2020 and the EEA/EMEP [44] global data in 2021. We combine these averages with urban-to-average or rural-to-average ratios, calculated based on Patella et al. [115] which used emission generation and energy consumption data from Italy in 2015. The average emission generation for Patella et al. [115] is derived by applying the Equation 6.3.

$$\bar{e}_i = \frac{E_i}{D_i} \qquad [6.3]$$

where:
$\bar{e}_i$ = Emission averages per powertrain i in g CO_2 equivalent per km
E_i = Total emissions per powertrain i in g CO_2 equivalent
D_i = Total distance traveled per powertrain i in km
In turn, to derive our emission baseline per road type and powertrain, we apply the Equation 6.4.

$$e_{ri} = \bar{e}_i \times f_{ri} \qquad [6.4]$$

where:
e_{ri} = Emission generation per road type r and powertrain i in g fuel per km
$\bar{e}_i$ = Average emission generation per powertrain i in g fuel per km
f_{ri} = Urban/rural-to-average factor per road type r and per powertrain i
Additionally, we assume the energy mix of Berlin and Brandenburg to be 100% based on renewable energy by 2050 and conclude the driving-related emissions of BEVs to be 0 grams of CO_2 equivalent per kilometer. Regarding the HEV type, we assume that urban streets are operated electrically and rural streets gasoline-based, similar to [115]. We classify streets within the city of Berlin as urban, all other streets as rural.

Driving-related energy consumption. Table 6.3 provides an overview of the energy consumption per road and powertrain type. We derive our energy consumption baseline by assuming the German averages of IEA [79, 80] and the urban-to-average (and rural-to-average) ratio from Patella et al. [115]. We assume the same urban-to-average and rural-to-average factors as for emission generation.

Vehicle Type	Our Baseline		Patella et al. [115]			IEA [79, 80]	EEA/EMEP [44]
	Urban	Rural	Urban	Rural	Average	Average	Average
	in g fuel/km, Wh/km (BEV)						
Gasoline	80.0	47.6	84.52	50.49	70.75	67	70
Diesel	65.0	47.6	69.85	50.16	62.28	58	60
LPG	74.5	63.3	75.31	64.65	70.78	70	57.5
BEV	175.4	204.6	150	175	162.5	190	-

Table 6.3: Average energy consumption per powertrain and road type.

In order to improve comparability between scenarios, we further transfer the various units into gasoline gallon equivalents (GGE). When transferring the kilowatt hours per kilometer into GGEs, we assume the conversion of 0.03 GGE per kilowatt hour [128]. For other powertrain types we use Equation 6.5.

$$C_{GGE,ri} = \frac{C_{G,ri}}{d_i} \times g_i \qquad [6.5]$$

where:

$C_{GGE,ri}$ = Consumption per road type r and powertrain i in GGE per km

$C_{G,ri}$ = Consumption per road type r and powertrain i in g fuel per km

d_i = Density per powertrain i in g fuel per gallon

g_i = GGE factor per powertrain i in GGE per gallon

For the calculation of Equation 6.4, we derive the density per fuel type from the European Environment Agency [44] and the gallon to GGE factor per fuel type from the U.S. Department of Energy [128]. As the density is provided in gram per liter, we transfer the unit to gram per gallon assuming the common gallon-to-liter conversion of 3.785 (e.g., [49]).

- Volume assumptions: 1 gallon diesel = 1.12 GGE, 1 gallon LPG = 0.74 [128]
- Density assumptions: 1 gallon gasoline = 2,839.1g gasoline, 1 gallon diesel = 3,179.7g diesel, 1 gallon LPG = 1,968.4g LPG, transferred from g/l to g/gal [44]

This results in our baseline of energy consumption in GGE per kilometer, see Table 6.4.

Vehicle Type	Our Baseline	
	Urban	Rural
	in GGE/km	
Gasoline	0.0282	0.0168
Diesel	0.0228	0.0168
LPG	0.0280	0.0238
BEV	0.0084	0.0097

Table 6.4: Energy consumption per powertrain and road type.

AV-related efficiency improvements. While the increased computational power demand of SAVs leads to an increment of greenhouse gas emissions, findings by Gawron et al. [52] in their life-cycle assessment of SAVs indicate that these impacts are compensated by improved driving and traffic behavior. This results in a net reduction of driving-related emissions of 9.1% for internal combustion engines vehicles (ICEVs) and 8.5% for BEVs as well as a net reduction of driving-related energy consumption of 8.9% for ICEVs and 8.5% for BEVs [52]. Consequently, the AV-related increase of energy consumption and emission generation (e.g. build-in computers), have been included in our calculations by incorporating the outlined net reduction figures. The net reduction are assumed for the introduction of a medium subsystem of autonomous driving [52].

Non driving-related emissions. Figure 6.10 illustrates additional non driving-related emissions related to their construction, maintenance and end-of-life phases. As a baseline for emissions per kilometer of Figure 6.10 a medium size passenger car with a lifespan of 15 years and 150,000 kilometer is assumed [115]. Similar assumptions have been made in comparable studies (e.g., [19, 60, 65, 87, 137]). Therefore, we avoid differentiating between emissions per vehicle and emissions per kilometer driven as the life-cycle assumption incorporates demand of vehicles implicitly.

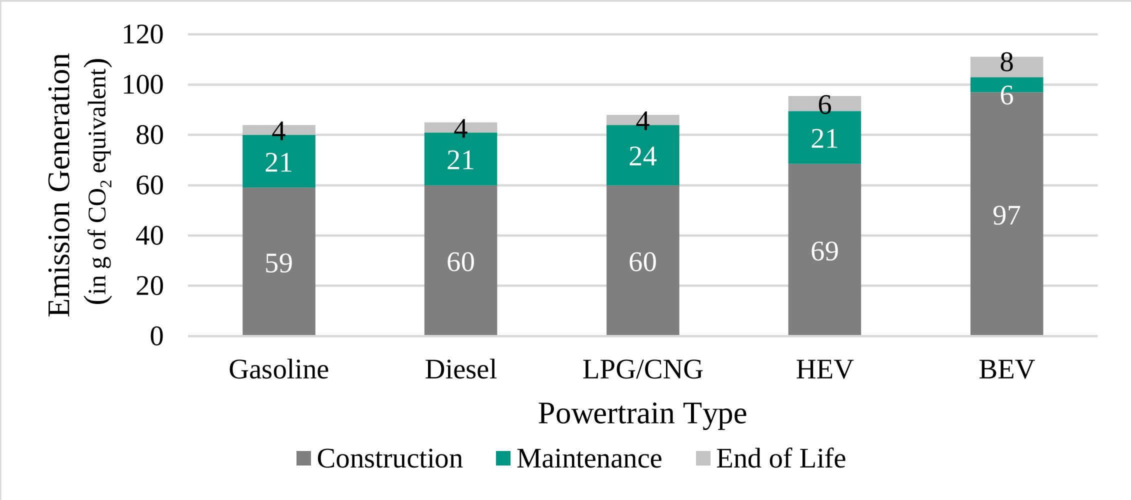


Figure 6.10: Life-cycle emissions per powertrain taken from Patella et al. [115].

We derive the driving-related energy consumption as in Equation 6.6, the driving-related emission generation as in Equation 6.7 and the total expected life-cycle emission generation as in Equation 6.8, while accounting for efficiency increases per automation level and powertrain type.

$$C_{Driving} = \sum_{r=1}^{m} \sum_{i=1}^{n} \sum_{t=1}^{o} D_{rit} \times c_{ri} \times g_{1it} \qquad [6.6]$$

$$E_{Driving} = \sum_{r=1}^{m} \sum_{i=1}^{n} \sum_{t=1}^{o} D_{rit} \times e_{driving,ri} \times g_{2it} \qquad [6.7]$$

$$E_{Life-Cycle} = \sum_{i=1}^{n} D_i \times (e_{Construction,i} + e_{Manufacturing,i} + e_{End-of-life,i}) + E_{Driving} \qquad [6.8]$$

where:

$C_{Driving}$ = Driving-related energy consumption in GGE

$E_{Driving}$ = Driving-related emissions in g of CO_2eq

$E_{Life-Cycle}$ = Total life-cycle emissions in g of CO_2eq

D_{ri} = Total distance traveled per road type r and powertrain i in km

c_{ri} = Driving-related energy consumption factor per road type r and powertrain i in GGE per km

$e_{driving,ri}$ = Driving-related emission factor per road type r and powertrain i in g of CO_2eq per km

$e_{construction,i}$ = Construction-related emission factor per powertrain i in g of CO_2eq per km

$e_{manufacturing,i}$ = Maintenance-related emission factor per powertrain i in g of CO_2eq per km

$e_{end-of-life,i}$ = End-of-life-related emission factor per powertrain i in g of CO_2eq per km

g_{1it} = Driving-related energy efficiency factor per automation level t and powertrain i

g_{2it} = Driving-related emission efficiency factor per automation level t and powertrain i

6.1.4 Sustainability Impacts of Scenario Results

In the following, we outline how the simulation results can be transferred into sustainability impacts. We base our calculations on the comparison of total vehicle kilometer traveled and apply calculations as outlined in Chapter 6.1.3. Additionally, as all numbers are based on the 10% Open Berlin Scenario, we focus on a relative comparison and observable trends, similar to Section 6.1.2.

Driving-related energy consumption. First, we quantify the aggregate energy consumption for each scenario. The outcomes per scenario, comparing the unchanged powertrain split and the 100% BEV assumption, can be seen in Figure 6.11. It becomes evident that the introduction of area-based SAV scenarios results in a decrease in total energy consumption by 1.5% (SC1.1) up to 1.8% (SC1.2), where the initial increase of total distance traveled is being overcompensated by efficiency improvements. A more pronounced effect can be observed in the 100% SAV scenarios. For SC1.3 a reduction of up to 7.7% in overall energy consumption results, owing to assumed efficiency increases of SAVs. The energy savings are enhanced when contrasting SC3.3 with SC3.0, revealing a decrease by 12.2%. This is related to the decrease in total vehicle kilometer, owing to increased population and travel density, combined with our assumptions of increased energy efficiency of SAVs.

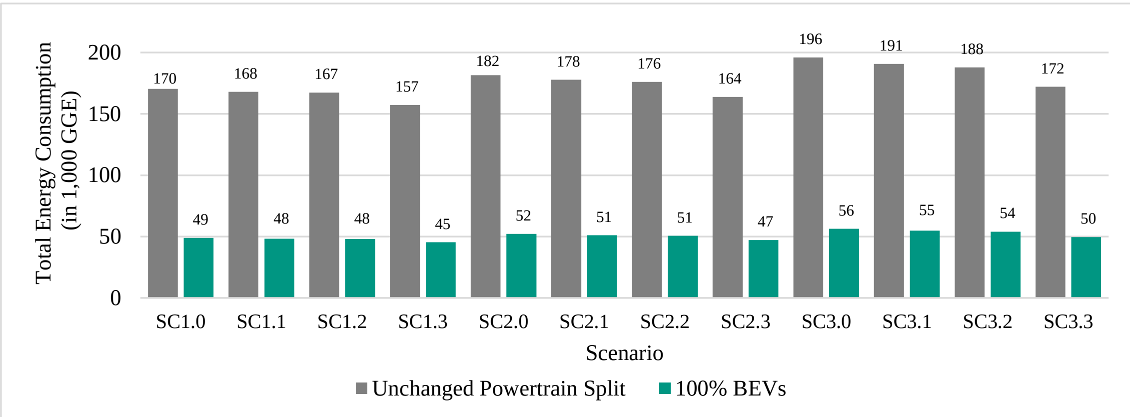


Figure 6.11: Daily energy consumption per scenario comparing the unchanged and 100% BEV powertrain split.

Additionally, Figure 6.11 allows to contrast our findings with the assumption of complete BEV adoption. The proportional increase or decrease in energy consumption across scenarios remains nearly consistent with the unchanged powertrain split scenario. When comparing SC1.1 and SC1.0, a decrease of 1.5% in the unchanged powertrain scenario results in a decrease of 1.4% for the 100% BEV split assumption. Similarly, a decrease of 7.4% in the 100% BEV split (compared to the 7.7% for an unchanged powertrain split) results when contrasting SC1.3 to SC1.0. The changes are related to different AV-related efficiency assumptions per powertrain (9.1% for ICEVs and 8.5% for BEVs). In turn, we can observe that the BEV assumption results in a reduction of overall energy consumption of 71.2% to 71.3% across all scenarios when compared to the unchanged powertrain scenario.

Driving-related emission generation. Secondly, we quantify the aggregate driving-related emissions of private cars and SAVs for each scenario. The outcomes are expressed in terms of grams of CO_2 equivalent, as elaborated in Chapter 6.1.3. As illustrated in Figure 6.12, assuming an unchanged powertrain split, the predominant sources of emissions are vehicles powered by gasoline and diesel, consistent with their combined contribution of 98.6% of all kilometers driven. Moreover, the reduction increases with higher SAV shares. The savings range from 1.6% (SC1.1 versus SC1.0) to 2.7% (SC3.1 versus SC3.0) comparing the scenarios with the smallest SAV-zone against the non SAV baselines. Similarly, a reduction of 2.0% (SC1.2 versus SC1.0) to 4.3% (SC3.2 versus SC3.0) can be derived in the intermediate scenario of SAV introduction. The highest decrease of 8.0% (SC1.3 versus SC1.0) to 12.4% (SC3.3 versus SC3.0) results for the three 100% SAV scenarios.

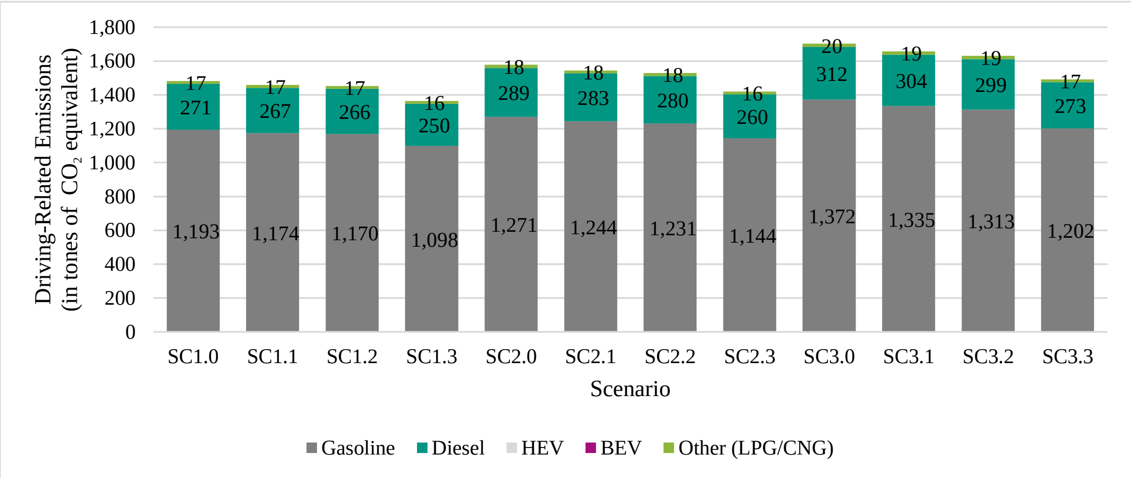


Figure 6.12: Daily driving-related emissions per scenario assuming the unchanged powertrain split.

Based on our assumption that the German electricity mix of 2050 will be entirely based on renewable energy sources, the observation for 100% BEVs results in zero driving-related emissions. In turn, there are no assumed sustainability impacts associated with SAVs from driving, which is why the 100% BEV comparison is not included in Figure 6.12.

Non driving-related emissions. Thirdly, we calculate the expected non driving-related emission generation. When combined with our driving-related emissions, we conclude the total life-cycle emissions as described in Chapter 6.1.3.

Before comparing the total emissions per scenario, we outline the non driving-related emission shares as these vary in particular in regards to the 100% BEV assumption, see Figure 6.13. In a 100% BEV-based car fleet, the non driving-related emissions are 31.7% higher across all scenarios compared to assuming the unchanged powertrain split scenario. In regards to SAV-related sustainability impacts, the SAV introduction leads to a different dynamic, compared to driving-related emission observations. This is due to the efficiency gains from Gawron et al. [52] being primarily related to driving-efficiency increases. We observe an increase of total non driving-related emissions ranging from 0.8% for SC1.1 to 2.8% for SC1.2, compared to SC1.0. SC1.3 in turn shows an reduced increase of 1.3% related to the reduced travel distanced increase. Accounting for our

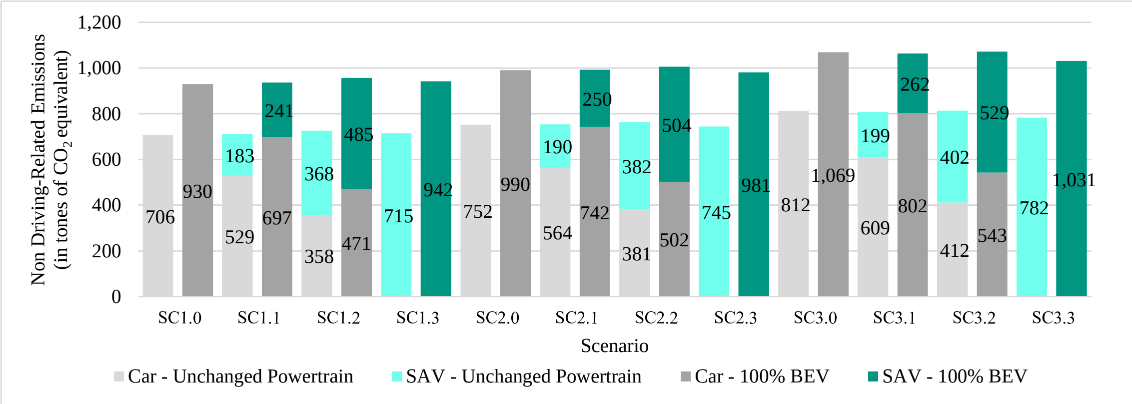


Figure 6.13: Daily non driving-related emissions per scenario comparing an the unchanged and 100% BEV powertrain split.

travel demand projections, we can observe minor emission reduction of up to 3.6%, contrasting SC3.3 to SC3.0.

Next, we examine the emissions generated by combining both non-driving and driving-related sources. In the scenario with the unchanged powertrain split, driving-related emissions account for 67.7% of total emissions, while in our 100% BEV scenario, all emissions are non-driving related. When contrasting the influence of SAV introduction for the unchanged powertrain perspectives, we identify reduced sustainability impacts compared to the exclusive consideration of driving-related emissions. We derive emission reductions of 5.0% (versus 8.0%) comparing SC1.3 with SC1.0, 7.1% (versus 10.0%) comparing SC2.3 with SC2.0 and 9.6% (versus 12.4%) comparing SC3.3 with SC3.0. This flattening of emission reduction is caused by the diminished relative savings of non driving-related emissions. Analyzing the total emissions caused by private cars against SAVs underlines the positive effect on emissions with the increase of SAV-share. Figure 6.14 shows an overview of total emissions across all scenarios and both the unchanged and 100% BEV powertrain split. Similar to previous analyses, the impact is further enhanced for scenarios including travel demand increases. This effect is observable in the same way for both the unchanged powertrain split scenario and the 100% BEV assumption, see Figure 6.14.

Additionally, we outline the impact of powertrain variations alongside various levels of SAV introduction. We see a positive impact of SAV introduction for the unchanged powertrain split scenario with decreases ranging from 0.8% (SC1.1 over SC1.0) to 9.6% (SC3.3 over SC3.0). In contrast to that, the sustainability impact of SAV introduction for the 100% BEV consideration ranges from a emission increase of 2.8% (SC1.1 over SC1.0) to a emission decrease of 3.6% (SC3.3 over SC3.0). Lastly, when comparing emissions without SAVs and the current powertrain split to a 100% BEV-based SAV introduction, we observe a emission reduction ranging from 56.3% (SC1.3 over SC1.0) up to 59.0% (SC3.3 over SC3.0). Consequently, the combined sustainability impact of BEVs paired with the 100% SAV introduction leads to the highest reduction of CO_2 emissions.

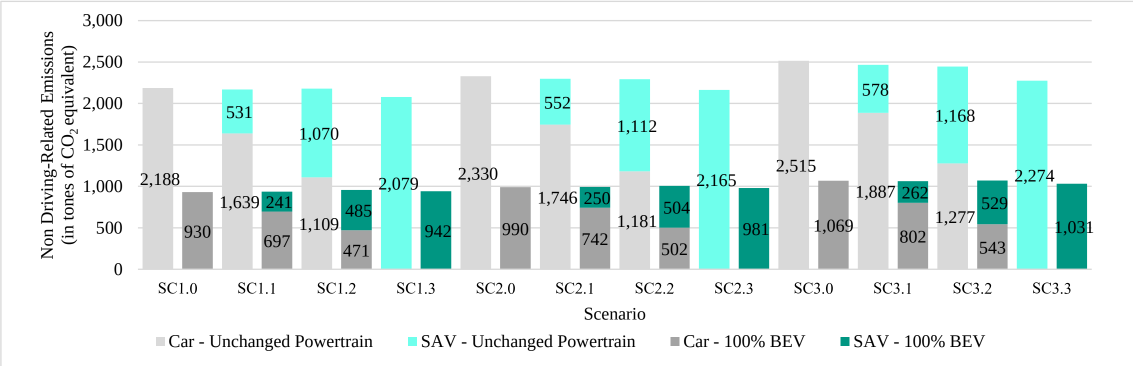


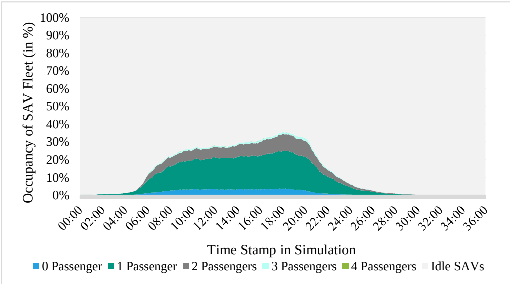
Figure 6.14: Daily life-cycle emissions per scenario comparing an the unchanged and 100% BEV powertrain split

6.1.5 Additional Analysis of Scenario Modifications

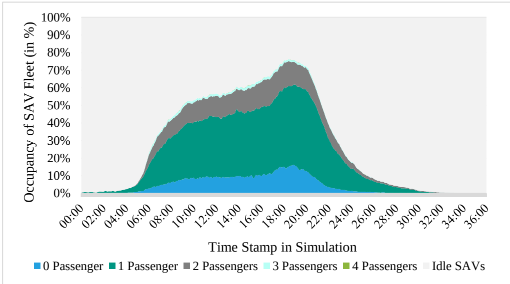
In the following, we examine impacts of three main scenario modifications: a decrease in SAV fleet size, an alteration in vehicle seating capacity from four to six, and the mandatory inclusion of hubs where idle SAVs must return to. Due to our constrained computational resources, we employ the 1% Open Berlin Scenario and run 2 iterations, consistent with our core scenarios. We maintain the simulation settings from SC1.3, as detailed in Chapter 5. Further fine-granular modifications are not tested, being out of scope of our study. After providing a concise overview of the foundational effects of these adjustments, such as the impacts on total vehicle distance covered and the occupancy rate, we delve into the impacts of these changes in regards to our sustainability indicators.

Impacts of changed fleet size. First, we analyze the results from adjusting the fleet size to 60%, 40% and 20% oppose to the ideal vehicle size derived from MATSim. As the fleet size of actively used vehicles by MATSim has been 7,199 SAVs in our SC1.3 of the 1% Open Berlin Scenario, this results in fleet sizes of 4,320 (60%) of 2,880 (40%) and 1,440 (20%), rounded to the next highest figure.

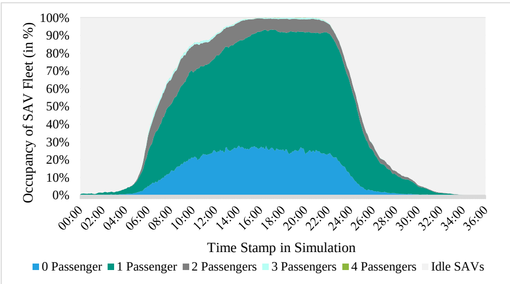
We observe an increase of vehicle kilometers of 7.2% (60% fleet), 28.3% (40% fleet) and 14.1% (20% fleet). In case of the 40% and 60% variation this is primarily related to inefficient routing and agent pick ups, as indicated by higher shares of empty or single passenger occupation ratios. In turn, the modification of a 20% fleet increases the occupation rate while being forced to take detours in order to cover the overall travel demand, as outlined in the following. We observe a distance ratio occupying zero or one passenger of 75.5% in our SC1.3 baseline, compared to 79.0% (60% fleet size), 88.9% (40% fleet size) and 65.8% (20% fleet size). Overall occupancy levels amount to 1.20 for our SC1.3 baseline, compared to 1.12 (60% fleet), 0.91 (40% fleet) and 1.34 (20% fleet). Consequently, the 20% SAV fleet modification can offer higher occupation averages. It has to be noted that the general occupation rate for the 1% Testing Model SC1.3 (1.20) is lower than the 10% Model SC1.3 (1.60), revealing notable inconsistencies between the 1% and 10% model. Consequently, we focus on the relative changes within the 1% Open Berlin Scenario and do not directly compare it to our 10% Open Berlin Scenario analyses. Despite the relative



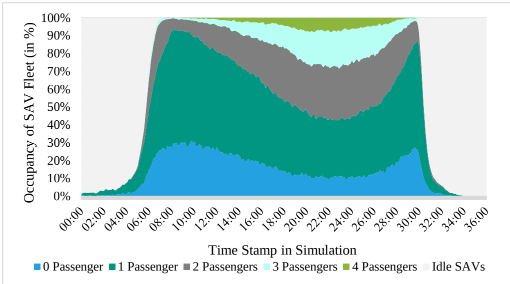
(a) SC1.3 baseline.



(b) SC1.3 60% fleet size.



(c) SC1.3 40% fleet size.



(d) SC1.3 20% fleet size.

Figure 6.15: Vehicle occupancy per SAV fleet size modification, graphic adapted from the output files of the Open Berlin Scenario [146].

increase of occupancy levels, overall (absolute) vehicle kilometers increase for most occupation levels of the 20% fleet size modification, except for single passenger travel. The absolute vehicle distances variations per occupation level range from a decrease of 18.3% (one passenger) to an increase of 178.7% (zero passengers) and 349.2% (three passengers), when comparing the 20% fleet modification to the SC1.3 baseline. This explains the increase of overall kilometers driven despite an increase of occupation level. Figure 6.15 shows that especially the 20% fleet operates at its utilization maximum for long periods of time forcing an increase in higher levels of occupancy. Similarly, the 40% modifications operates at almost 100% utilization of the SAV fleet between 4:00pm and 9:00pm. This results in high SAV waiting times ranging from an increase of SC1.3 of 15.2% (60% fleet size) to 350.2% (20% fleet size). Additionally, for the 20% and 40% variations, we observe high levels of traffic well beyond the 24:00 hours mark (internal simulation time), see Figure 6.15. The traffic significantly influences travel patterns on the following day.

Our analyses indicate that modifications of fleet sizes defined by MATSim result in decreased service levels for agents and increased total vehicles kilometers. The enhanced total vehicle distances are caused by additional detours as outlined by comparing occupancy levels to total absolute distances traveled. In alignment to the rise in total vehicle distance traveled, the modifications result in increased energy consumption and emission generation, as illustrated in Table 6.5. We can observe an increase in energy consumption and emission production ranging from 7.2% (20%) to 28.3% (40% fleet), compared to the baseline SC1.3. However, as outlined, the 20% fleet size modification has to be considered with caution due to its limited applicability related to extreme waiting times and high traffic beyond the 24:00 hours mark of simulation time.

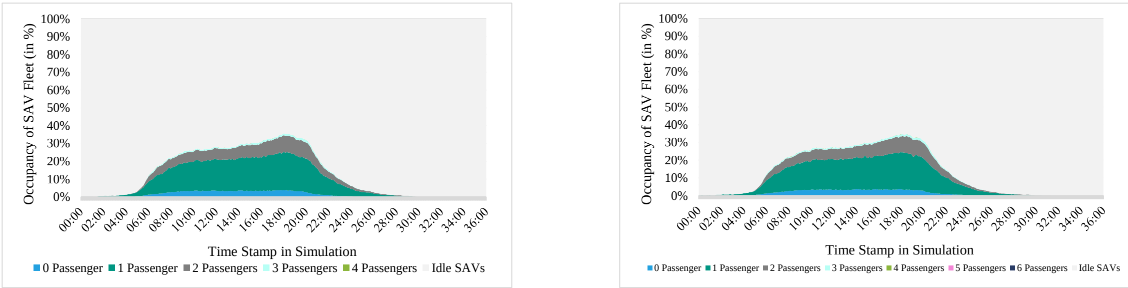
Scenario	Energy Consumption	Emission Generation	Delta to SC1.3
	in 1,000 GGE	in tones of CO_2 equivalent	in %
SC1.3	20.0	264.7	-
SC1.3 60% fleet	22.8	301.9	14.1%
SC1.3 40% fleet	25.7	339.6	28.3%
SC1.3 20% fleet	21.5	283.6	7.2%
SC1.3 6 seats	20.0	264.6	-0.03%
SC1.3 Hubs	29.1	384.6	45.3%

Table 6.5: Overview of sustainability impacts of each scenario modification.

Impacts of changed vehicle size. Introducing vehicles that suit six instead of four passengers left the total number of required SAVs almost unchanged. A decrease from 8,199 to 8,192 SAVs results. Similarly, the total vehicle kilometers is reduced by 0.03%. Displayed in Figure 6.16, we can see marginal changes being related to the comparatively small portion of SAVs operating with more than four passengers (0.002%). Consequently, the distribution of occupancy over time is almost unchanged compared to SC1.3. Based on our findings of the core scenarios, settings like SAVs staying at the last location of each trip indicate SAV travel routes to adjust towards individual travel behavior. This in turn, explains the small demand for shared driving above 4 passengers. However, it needs to be emphasized that with an increase in population density this demand might increase, e.g. due to more passengers sharing similar routes such as commuting to the city of Berlin. Similar to previous figures, the empty distance ratio, total passenger hours and waiting times show little variations, when comparing the modified six-seat SAV scenario to the SC1.3 baseline.

As illustrated in Table 6.5, the modified scenario, in tandem with the decrease in total vehicle distance traveled, demonstrates slight improvements in terms of energy consumption and emission generation with a reduction of 0.03% for both indicators, compared to the baseline SC1.3. However, this analysis does not incorporate the increase in emissions per kilometer and energy demand of the six-seated vehicles due to the increase of vehicle size and weight of the vehicle. This indicates that the 0.03% emission and energy generation savings might be overcompensated by additional energy demand. Similarly, Vosooghi et al. [130] conclude the standard of four seats to be the better performing alternative.

Impacts of mandatory SAV hubs for idle vehicles. As an optional setting of MATSim, SAV hubs describe a system of 6,416 links spread across the Berlin city area. For the 1% Open Berlin Scenario, 10,000 SAVs are programmed to return to the closest hub when idle. 98% of the hubs contain one SAV. 140 of the hubs host more than one SAV, while the biggest hub covers 79 SAVs. Therefore, the hub system can be described as widely spread across the city of Berlin, comparable to a network of charging stations in case of fully electric SAVs. A visualization of the initial SAV placements can be seen in Figure 6.17. The according geographical data is extracted from the SAV vehicles file, see Section 5.1.



(a) SC1.3 four seats.

(b) SC1.3 six seats.

Figure 6.16: Vehicle occupancy per SAV vehicle size, graphic adapted from the output files of the Open Berlin Scenario [146].

Introducing mandatory SAV hubs for idle vehicles leads to an increased SAV distance traveled of 45.3%, compared to our SC1.3 benchmark. The increased distance traveled is mainly driven by the additional empty travel from and to the defined hubs, accounting for 32.8% of overall SAV distance traveled. In our SC1.3 baseline the empty distance ratio equals 6.8%, owing to reduced additional travel as vehicles stay at their current location when idle. Next to the increase in empty distance traveled, the occupied distance has increased by 4.7%, related to a surge in distance traveled while occupying one passenger (13.0% increase over SC1.3). This results in a total occupation ratio of 1.15 compared to the SC1.3 baseline of 1.20. Consequently, it is not only the empty rides but also the traveled distance with in-car passengers that have increased, potentially related to inefficient routes and detours to pick up other passengers. Accordingly, the total passenger hours traveled increase by 47.2%. Lastly, we observe an increase in energy consumption and emission generation of 45.3% each, compared to the SC1.3 baseline.

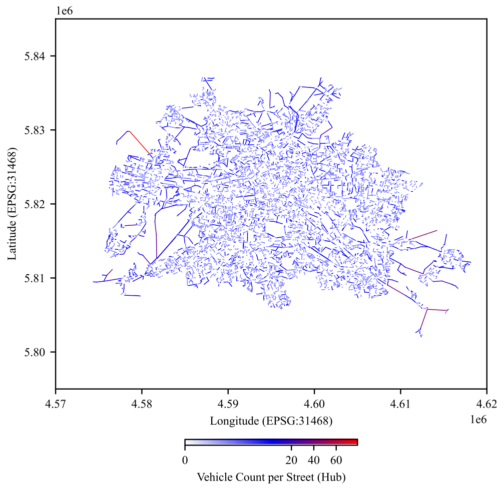


Figure 6.17: Spread of SAV hubs across the area of Berlin city.

6.2 Evaluation

In the following, we evaluate our findings in alignment with the three fundamental pillars of our approach. Therefore, we evaluate the demand forecast in Section 6.2.1, the simulation in Section 6.2.2 and the exploration of the sustainability impacts in Section 6.2.3. We place particular attention to significant variations, and a comparative assessment of our results against other studies in the field.

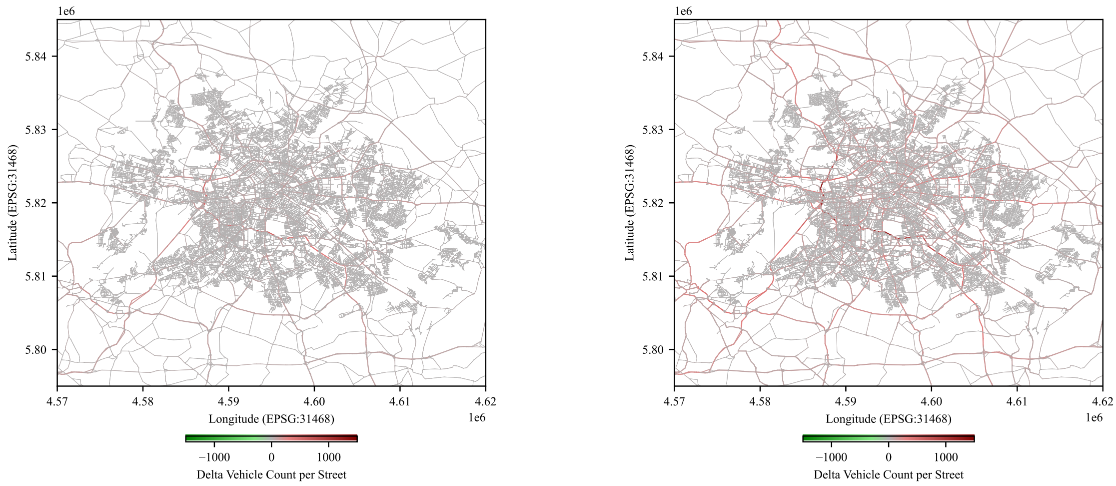
6.2.1 Evaluation of Demand Forecast

Initially, we compare our general approach and general results with alternative research, followed by an outline of the impacts of our forecast implementation to the MATSim simulation.

Comparison of our general approach and results to alternative research. It is important to note that our forecast primarily focuses on population growth and age-related travel behavior. However, this approach overlooks the potential impact of behavioral shifts towards the adoption of SAVs. Lutin et al. [101] suggest that the elimination of the requirement for a driver's license could lead to a significant increase in travel demand in AV scenarios [115]. Consequently, this could change our assumed age related travel patterns. Sonnleitner et al. [121] conclude that the enhanced capabilities of SAVs may result in a potential increase in road traffic of up to 20% as people are willing to travel longer distances using SAVs. Massar et al. [33] estimate the total distance traveled to increase by up to 20% due to enhanced road capacity, decreased travel-related costs, and a reduction in perceived travel duration. Although based on different assumptions, we derive travel demand increases of up to 14.9% in comparison.

Other scholars, including Cokyasar et al. [36], have identified a correlation between the rise in the number of trips and population growth. This aligns with our methodology, which uses population growth as a primary driver. Our approach refines this by integrating age-based travel demand, adding a layer of granularity. Similarly, Hidaka and Shiga [68] consider factors such as age compositions and the age-related decrease in individual travel requirements. They also incorporate the decrease of relative driver's license ownership and regional influences [68]. As a result, their methodology offers a more comprehensive set of input variables. An alternative approach to derive a prognosis of travel demand is by forecasting developments of trip purposes such as work, education and leisure related travels [135]. Lastly, Winkler and Mocanu [135] conclude a German wide increase in car-based passenger distance traveled of 6% from 2010 to 2040, compared to our 6.6% low-2050 and 14.9% high-2050 assumptions.

Impacts of our forecast to the MATSim simulation. Changes of our implementation of the travel demand increase reveal significant impacts to traffic density compared to the baseline simulation. We see an average increase of vehicles per link of 15.7 (SC2.0) to 36.1 vehicles (SC3.0) with current traffic levels of 242 vehicles per link (SC1.0). Furthermore, we observe a maximum increase of 613 vehicles for SC2.0 and 1,497 vehicles for SC3.0. This corresponds to a relative increase of 6.1% for SC2.0 and 14.9% for SC3.0 compared to the link's previous vehicle volume. As depicted in Figure 6.18, the increase of traffic is spread equally throughout Berlin for both SC2.0 and SC3.0. In terms of absolute numbers, the main traffic routes experience the highest

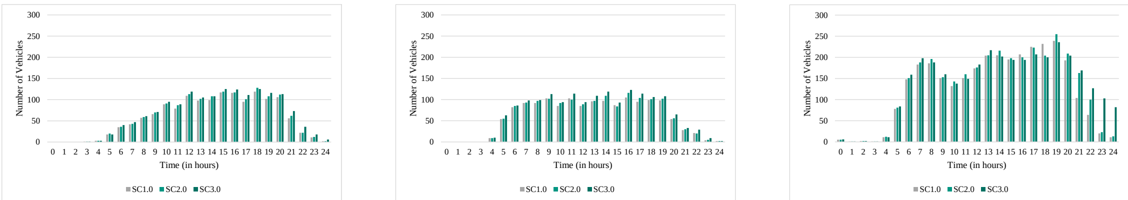


(a) Volume increase in SC2.0. (b) Volume increase in SC3.0.

Figure 6.18: Delta in vehicle volume per street compared to the SC1.0 baseline.

increase, while in proportion to current traffic occurrence. We derive our traffic per link data from the output events file, see Section 5.3.

Aiming to derive a more detailed understanding of simulation impacts, we further analyze traffic volumes of specific links. Similar to Ziemke et al. [146], we contrast the link volume per time stamp across their three randomly selected streets: the "Leipziger Straße" in Berlin city (link 69438), the "Märkische Allee" (link 76921) and the northern inner motorway ring A100 (link 125775), see Figure 6.19.



(a) Leipziger Straße. (b) Märkische Alle. (c) Northern inner motorway A100.

Figure 6.19: Link volume across three exemplary streets contrasting SC1.0, SC2.0 and SC3.0 adapted from Ziemke et al. [146].

We see a noticeable rise in traffic based on individual forecast implementation, with increases of up to 12.4% (SC2.0 compared to SC1.0) and 22.7% (SC3.0 compared to SC1.0) when examining the hourly traffic across all links until 8:00 pm. An even increased impact can be observe due to the induced traffic of SC3.0, particularly on the northern inner motorway ring during the evening hours of 11:00pm to 12:00 pm. The hourly vehicle count of 20 and 11 surged to 103 and 82 vehicles, comparing SC3.0 to SC1.0. This reveals that the increase of traffic causes a delay of periods of high traffic for single heavily used routes. Consequently, these shifts would result in further traffic delays on previously entered links per vehicle route, emphasizing the complexity of MATSim and side-effects of the increase in travel demand.

To examine if traffic delays are cause of an overall shift in departures, we analyse departure times per time stamp, see Figure 6.20.

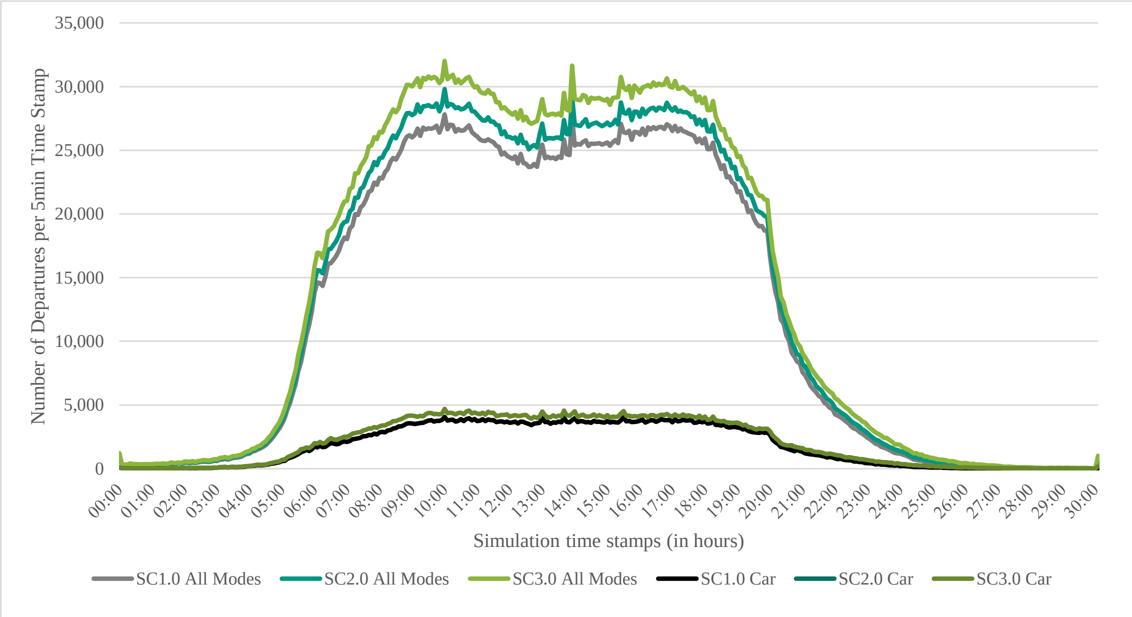


Figure 6.20: Derivation of departures of all travel modes in one simulation day per 5min time stamp, graphic adapted from the output files of the Open Berlin Scenario [146].

We compare the impact of implementing the two travel demand forecasts in SC2.0 and SC3.0 to our SC1.0 baseline. After introducing our 6.6% travel demand surge (SC2.0), hourly departures rise in a range from 5.6% to a 8.1% between 12:00am to 8:00pm. However, similar to our analysis of traffic occurrence on single links, we see travel spikes lasting for a longer period of time. This results in a relative increase of 6.7% to 17.1% in hourly departures from 8:00pm to 12:00pm. In case of the 14.9% travel demand increase (SC3.0), hourly departures increase from 12.5% to 19.9% in the time range from 12:00am to 08:00pm and 15.7% to 47.8% from 08:00pm to 12:00am. It has to be emphasized that the high relative increases towards the end of the day represent a reduced absolute number of hourly departures. For instance, we see 20.8 thousand departures between 11:00pm to 12:00am compared to the peak of 321.0 thousand departures from 10:00am to 11:00am in SC1.0. Lastly, we see more departures being transferred into the next simulation day, as indicated by departures in the simulation time range from 24:00h to 30:00h in Figure 6.20. This amounts to 20.3 thousand departures being transferred to the next day for SC2.0 and 30.9 thousand for SC3.0, compared to 16.1 thousand in SC1.0. Similarly, car-based hourly departures increase ranging from 4.5% to 8.4% in the time range from 12:00am to 08:00pm and 6.7% to 21.5% from 08:00pm to 12:00am, comparing SC2.0 to SC1.0. Contrasting SC3.0 to SC1.0, car-based hourly departures increase ranging from 9.8% to 19.1% from 12:00am to 08:00pm and 16.8% to 62.4% from 08:00pm to 12:00am. A total of 4.1 thousand car-based departures are transferred to the next day for SC2.0 and 6.7 thousand for SC3.0, compared to 3.1 thousand in SC1.0. Hourly departures and vehicles on route are extracted from the leg histogram file, see Section 5.3.

Figure 6.21 shows that traffic spikes experience an even enhanced surge, related to the outlined local traffic spikes and departure shifts leading to prolonged evening traffic. When analyzing the number of vehicles being on the road, we see an even enhanced pattern of shifts towards evening traffic. Car-based hourly traffic increases ranging from 4.6% to 13.9% from 12:00am to 08:00pm and 17.9% to 23.4% from 08:00pm to 12:00am, comparing SC2.0 to SC1.0. Contrasting SC3.0 to SC1.0, car-based hourly departures increase ranging from 9.7% to 45.3% from 12:00am to 08:00pm and 59.1% to 125.0% from 08:00pm to 12:00am. Consequently, we see additional increases of traffic when coupled with the high travel demand forecast. A total of 50.7 thousand cars on the route are transferred to the next day for SC2.0 and 22.1 thousand for SC3.0, compared to 16.4 thousand in SC1.0. After outlining the traffic shifts towards evening traffic, the general shape of traffic occurrence has stayed in line with the original simulation, see Figure 6.21.

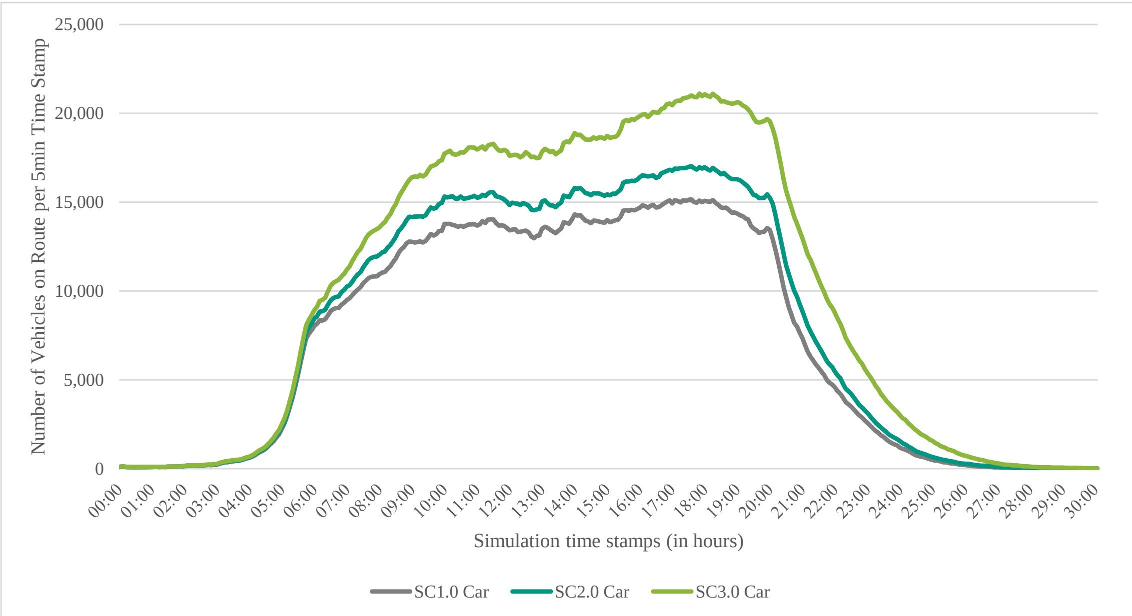


Figure 6.21: Derivation of private cars in traffic in one simulation day per 5min time stamp, graphic adapted from the output files of the Open Berlin Scenario [146].

Finally, we compare the impacts of our travel demand increase to the overall travel mode split. We see variations of up to 0.07% when comparing the total passenger kilometer increase to our intended travel demand increase. Differences of up to 0.29% can be observed when considering single traffic modes, see Table 6.6. The relative mode split stayed consistent with variations below 0.05%. The average trip distance stayed within a range of 9,493 to 9,497 meters for SC1.0, SC2.0 and SC3.0.

Scenario	Intended	Total	Bicycle	Car	Public Transport	Ride	Walk
SC2.0	6.56%	6.48%	6.54%	6.48%	6.50%	6.56%	6.59%
SC3.0	14.89%	14.84%	14.60%	14.96%	14.95%	14.73%	15.07%

Table 6.6: Passenger kilometers increase after forecast implementation.

6.2.2 Evaluation of the Simulation Results

Similar to Subsection 6.2.1, we initially compare our general approach and results with findings of other scholars. Secondly, we evaluate simulation-related impacts of our scenario implementation.

Comparison of our general approach to alternative research. One assumption of the SAV scenarios is that the adoption of SAVs can be steered through regulatory interventions, such as SAV-exclusive zones. Similarly, researches have implemented regulatory interventions such as a city wide SAV introduction or a replacement of specific travel modes and activities (e.g., [145, 147, 20]).

Pakusch et al. [113] and Harb et al. [63], doubt that car ownership will become an outdated model. In turn, a shared travel mode will rather be adopted to the expense of public transport [113]. While we observe an insignificant shift from public transport to SAV travel, our simulation did not confirm this second hypothesis. Nevertheless, the feasibility of realizing 100% SAV scenarios can be questioned. Alternatively, a hybrid combination of SAVs and private vehicles, as exemplified by our scenarios introducing smaller SAV zones, is another plausible outcome.

Furthermore, focusing on the perspective of AV efficiency, Patella et al. [115] considered 40% (urban roads) to 80% (highways) capacity increases which was not included in our simulations. Consequently, the increase in heavy traffic, discussed in Section 6.1.2, can be considered as conservative not directly incorporating capacity related efficiency increases of SAVs. In turn, an increase in road capacity, is usually followed by travel demand increase [136]. Consequently, the induced traffic demand might potentially overcompensate efficiency improvements related to capacity improvements. The efficiency increase in regards to general driving, however, has been incorporated implicitly through our efficiency increase assumptions based on Gawron et al. [52].

While we distinguish between an unchanged, a moderate and a high population growth to derive our travel demand forecasts (0% to 14.9% increase), it can be argued that a reduced future travel demand is realistic as well, driven by the advent of e.g., remote work [2, 31, 116]. Other researchers assume an increase in travel demand related to the availability of car-based mobility, the enhancement in willingness to travel with SAVs compared to non-AV cars as well as population growth in metropolitan areas, with travel demand rising from 6% to 20% (e.g., [36, 115, 121, 135]).

As the total vehicle kilometers describe a core element of our sustainability impact derivation, we compare our results to findings of other scholars. To isolate SAV impacts, we compare the change of vehicle kilometer not including the travel demand forecasts. A wide range of results can be derived from the current research body. Patella et al. [115] conclude total traffic kilometer variations to range from a 5.0% decrease in urban areas and 8.0% increase on highways in a 100% AV scenario. The decrease in urban areas can be attributed to a shift from urban to highway-based travel as higher capacity gains were applied to highways compared to urban roads [115]. They find a total increase of vehicle distance of 1% [115]. Since no travel demand forecast was incorporated, we can compare these results with our SC1.3, which concludes an increase of up to 1.3%, although assuming SAVs instead of AVs.

Liu et al. [98] analyze the SAV adoption based on variations of SAV pricing fares, as outlined in Chapter 3. They derive vehicle distance increases ranging from 9.8% to 15.7%, with SAV adoption ranging from 9.2% to 50.9%, relative to all mode trips (including non-car-based travel) [98]. Increased SAV-shares show reduced increase of vehicles distances in the analysis of Liu et al. [98], similar to our findings. We observe travel demand increases of 0.8% (69.4% SAV share of all travel modes) and 2.8% with 38.9% SAV share of all travel modes.

Martinez and Viegas [104] studied the impact of introducing SAVs and SAV shuttles in Lisbon in 2010/2011, as outlined in Chapter 3. Considering the SAV scenario, they conclude a decrease in vehicle distance traveled of up to 24.9% [104], in contrast to our 0.8% for the comparable SC1.3. This high decrease is also related to a shift from motorized vehicles (including e.g., motorcycles and taxis) towards walking and public transport next to SAVs. Consequently, additional impacts have been incorporated as an indirect influence of limiting travel mode choices to walking, public transport and SAVs.

Simulation-related impacts of our scenario implementation. We initially base our simulation on the thoroughly tested and calibrated Open Berlin Scenario [146]. As we introduce modifications, we already compare our results of traffic behavior to the unchanged, baseline scenario SC1.0 in Section 6.1.2. Independent of the previous discussed variables that directly or indirectly affect the sustainability impact of SAVs, waiting times can be contrasted, similar to Bischoff and Maciejewski [20].

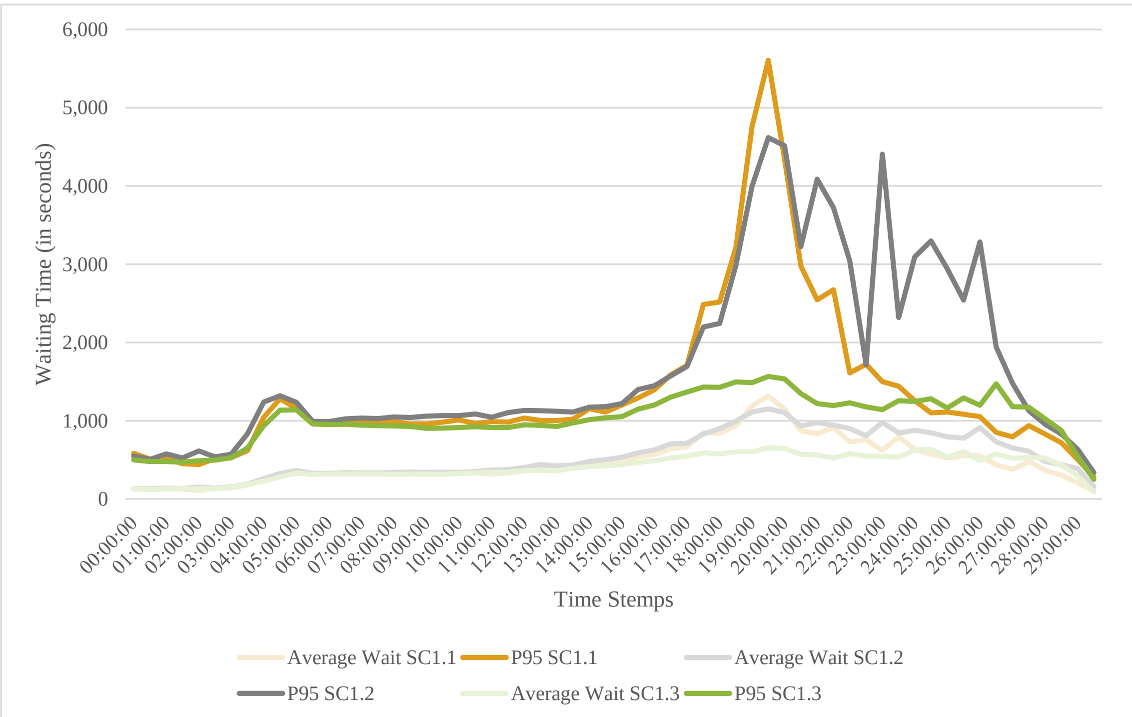
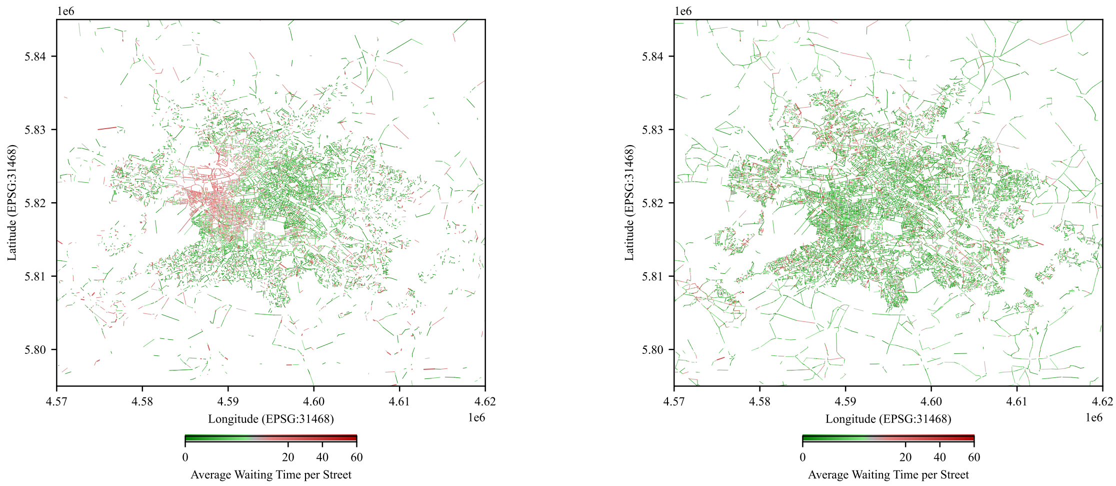


Figure 6.22: Average waiting times per SAV scenario, graphic adapted from the output files of the Open Berlin Scenario [146].

As depicted in Figure 6.22, especially for the partial SAV introduction, waiting times spike the highest. In turn, the increase of waiting times in the morning is comparatively low, owing to the fact that our large SAV fleet stays in close proximity to the last locations of agents over



(a) Average waiting time SC1.1.

(b) Average waiting time SC1.3.

Figure 6.23: A comparison of the average waiting time, contrasting the two scenarios of the lowest and highest SAV share.

night. Additionally, SC1.2 shows a comparatively long duration of high waiting times after the 6-8pm spike, owing to long travel distance between available SAVs. While the average waiting times increase to 22 minutes in SC1.1, the 95th percentile experiences waiting times of up to 93 minutes. This extended wait is due to insufficient nearby SAVs. With the introduction of the 100% SAV scenario a more wide-spread SAV fleet is able to overcompensate these areas of inefficiency, see Figure 6.23.

The SC1.3 scenario results in spikes of 20 minutes for the 95th percentile and ten minutes of average waiting times in the 6-8pm spike. In comparison, Bischoff and Maciejewski [20] found that the 95th percentile of waiting times were around 14 to 15 minutes in their analysis, which excluded all inter-rural traffic. However, for outer areas of Berlin city, they observe strong variations, with average waiting times reaching up to 20 minutes [20]. Considering this insight, we incorporate rural traffic. With that, areas that are less frequently accessed are being served by SAVs. This approach contrasts with only focusing on incoming and outgoing traffic in the Berlin city area and results in high waiting time spikes for reduced SAV adoption. Consequently, we see potential for improvement, particularly when serving agents with no available nearby SAVs. Waiting times can directly be access from the waiting stats file, see Section 5.3.

As Bischoff and Maciejewski [20] have conducted a SAV analysis for the Berlin City, we compare their 100% scenario statistics with key figures of our 100% SAV scenarios in the following. Bischoff and Maciejewski [20] conclude the average SAV to drive 274 kilometers (compared to our 203-216 kilometers in our scenarios), with a 13% empty ride share (compared to our 3% to 3.1%). The average trip distance was described with 9.1 kilometers (compared to our 11.0 kilometers), with a standard derivation of 88 kilometers (compared to our 134.8 to 136.6 kilometers) [20]. The differences can be attributed to the fact that Bischoff and Maciejewski [20] focused on the traffic affecting the Berlin city area, excluding any travel that is not entering or exiting the city (around

35% of the total trips). In turn, 35% of our considered SAV trips describe inter-rural trips, which explains our higher average trip distance. Additionally, Bischoff and Maciejewski [20] consider a fleet size of 100 thousand SAVs for a 100% Open Berlin Scenario. This is compared to our fleet sizes of up to 68.1 thousand SAVs, considering the 10% Open Berlin Scenario without incorporating travel demand increases. Consequently, incorporating the outer rural trips in our simulations significantly increases the required SAV fleet size. Additionally, a reduced average distance per vehicles results as trips are spread across a larger fleet of SAVs. A larger fleet size, coupled with SAVs remaining at the agents' home locations overnight, allows vehicles to better align with individual travel patterns. As a result, the share of empty trips decreases, but the total distance driven varies stronger based on the agents' travel habits.

6.2.3 Evaluation of the Sustainability Impacts

In the following, we compare our general approach with other scholars' before comparing the sustainability implications with results of the current research body.

Comparison of our general approach to alternative research. Initially, it has to be emphasized that results highly depend on assumptions regarding the energy consumption and emission generation of vehicles, therefore, providing varying emission reduction potentials for SAVs. While the emissions per powertrain split differ geographically and within studies, potential efficiency increases in the upcoming years until 2050 will have an impact on emissions and energy consumption per powertrain. In our analysis, we have incorporate changes in the powertrain split by contrasting the current powertrain split to a 100% BEV scenario, similar to Patella et al. [115]. However, efficiency increases for ICEVs have not been included. Consequently, optimistic assumptions of reduced emissions independent of the automation of cars may restrict the absolute sustainability impact of SAVs. Additionally, BEV emissions strongly depend on the share of renewable sources of the electricity mix [73]. While we assume to have a 100% renewable electricity mix by 2050, the current electricity mix of Germany equals to 41.1% in electricity production and 19.7% in electricity brutto consumption in 2021 [127]. As a result, BEVs generate considerable driving-related emissions, contrary to our 100% BEV assumptions.

Further approach-related assumptions influencing the sustainability impacts include the emission calculation baseline. In contrast to Huelsmann et al. [72], Kickhoefer [86] or Fagnant et al. [45], we do not differentiate between warm and cold-start emissions. Differentiating both could lead to more favorable conclusions regarding sustainability impact of SAVs. A constantly driving fleet of SAVs would benefit from reduced warm emissions, compared to the longer parking durations of private cars, not being used as consistently as a shared fleet. Instead, we mainly differentiate between rural and urban traffic, similar to other scholars (e.g., [48, 115, 139]). Therefore, we account for emission differences of up to 59.5% in case of gasoline emissions between rural and urban travel, see Table 6.2.

Another core assumption driving emissions per distance traveled is the assumed mileage. Andersson and Borjesson [10] consider the adoption of a 150,000 kilometer vehicle mileage as overly conservative, biasing the preference towards HEVs and ICEVs over BEVs. Similarly, Amatuni et al. [8] and Garon et al. [52] conclude an average life time mileage of 240,000 and 260,000 kilometer. Consequently, our mileage baseline leads to more conservative sustainability improvements while numerous scholars build upon the same assumption (e.g., [19, 60, 65, 87, 137]).

Comparison of derived sustainability impacts of other scholars. Fagnant et al. [45] conclude their SAV system to reduce CO emissions by 34% and total emission generation by 5.6%. As outlined in Chapter 3, Fagnant et al. [45] build their analyses on a artificial population. Consequently, the comparison falls short in representing real worlds scenarios. However, they replaced all car-based travel by SAVs, therefore, following a similar approach to our 100% SAV introduction.

Harper et al. [64] estimated energy use, emitted emissions and required parking with the introduction of AVs, see Chapter 3. They conclude the energy use and greenhouse gas emissions to increase to around 3% related to traffic increases as car owners allow AVs to travel longer distances for more affordable parking [64].

Liu et al. [98] analyzed the potential reduction of total greenhouse gas emission and energy consumption based on variations of SAV pricing fare, as outlined in Chapter 3. They derive a potential reduction of total emission generation of 16.8% and fuel consumption of 22.4% when contrasting an average light-duty non-SAV with its SAV counterpart and assuming no changes in total vehicle kilometers [98]. They observe vehicle distance increases being reduced with higher SAV shares [98]. This leads to a reduction in fuel consumption of up to 14.8% and emission generation reduction of up to 8.7% in case of a 50.9% SAV-share of total travel modes [98]. When compared to our SC1.2 with a 38.9% and SC1.3 with a 69.5% SAV-share of total agent trips, we conclude a energy consumption reduction of 1.8% to 7.7% and a emission generation reduction of 0.4% to 5.0%.

Martinez and Viegas [104] analyzed the introduction of SAVs to the city of Lisbon. Removing private cars, they considered one scenario introducing SAVs and a combined scenario of SAVs and automated shuttle buses, see Section 3. While they based their study on the current powertrain mix of 2011, they recognized a future shift towards electric SAVs to be realistic [104]. Since private cars, motorcycles and taxis not only being replaced by SAVs but also by public transport or walking, they conclude a reduced CO_2 emission generation of 32.3% in SAV scenario related to a reduction of total vehicle kilometer [104]. In comparison to that, our scenarios assume almost unchanged vehicle distance traveled, for scenario without considering forecasts, and tailpipe emissions to be reduced by 8.0% in the comparable SC1.3.

Patella et al. [115] derive a total emission reduction potential of 59.6% for their 100% electric AV scenario when compared to emissions of a current powertrain split which consists to 98.6% of gasoline, diesel and LPG-based vehicles in 2018. We see a powertrain split of 99.8% gasoline, diesel and LPG-base fleet for our 2011 baseline. When introducing our 100% SAV fleet, we derive a reduction in emission generation of 56.9% for our 100% BEV-based SAV fleet and unchanged traffic demand.

Additionally, it is noteworthy that scholars assumptions in efficiency gains through automation vary (e.g., based on eco-drive, platooning, driver and traffic behavior [88]) from more optimistic with greenhouse gas emission reductions of up to 30% in case of Massar et al. [105] or up to 40% for a 100% SAV scenario in case of Yao et al. [138] to less optimistic assumption of 8.1% emission reduction potential in case of Gawron et al [52]. In our analysis (as outlined in Chapter 5) we build on the conservative numbers of Gawron et al. [52].

In summary, our findings can be classified as moderate compared to alternative research. This fits our conservative approach of e.g., including moderate efficiency increases of AV related capabilities. In turn, the combination of a 100% SAV and BEV scenario results in even higher positive sustainability impacts which is attributed to the net zero emission assumption of BEVs in 2050.

7 Conclusion and Outlook

Using an agent-based simulation, we outline the sustainability impacts of three levels of SAV introduction to the private passenger transport sector of the wider area of Berlin and Brandenburg. We address gaps and improvement potentials of the current research body by building upon a calibrated simulation model that incorporates real world commuter and travel statistics. As current research frequently uses outdated travel data, this study generates a projection of three levels of travel demand of Berlin and Brandenburg for 2050. Moreover, we respond to the need for more sustainability analyses that consider multiple levels of SAV introduction. We introduce three levels of SAV-exclusive car-based traffic zones in our simulation scenarios. Lastly, we address the need for more comprehensive sustainability analyses by comparing driving-related energy consumption and emission generation as well as total life-cycle emissions. In doing so, we answer three research questions. First, we explore what approaches and essential inputs are available for SAV simulations. Second, we investigate how we can implement various levels of SAV introduction in these simulations. Lastly, we outline how different scenarios can be compared, with a special emphasis on evaluating their impacts on sustainability.

Our findings suggest that by implementing various SAV scenarios, there is a potential reduction ranging from 0.4% to 9.6% in emissions generation and 1.5% to 12.2% in energy consumption in the private passenger transport sector of Berlin and Brandenburg. Other studies have found varying potential impacts on emission generation, ranging from an increase of about 3% to a decrease of 32.3% (e.g., [45, 98, 104, 64]). Energy consumption impacts range from a potential increase up to 3% to a decrease of 14.8% (e.g., [98, 64]). These variations are attributed to changes in SAV share, efficiency, traffic, and powertrain assumptions. Furthermore, we observe that with a 100% BEV-based SAV fleet, the potential for emission reduction increases up to 56.9% and 59.0% when incorporating increased travel demand, compared to our baseline scenarios without SAVs. Following a similar approach, Patella et al. [115] concluded a emission reduction potential of 59.6% with the introduction of BEV-based AVs and no travel demand forecast. While these results promise benefits from the introduction of SAVs in the private passenger transport sector, we outline our limitations and potential future research in the following.

7.1 Limitations

This study does not provide a forecast of SAV adoption. It has to be emphasized that adoption forecasts vary a lot depending on underlying assumptions. For instance Dubey et al. [42] forecast 20% to 65% market share of Level 4 AVs in 2042 when assuming a 5% annual price decrease while Bansal et al. [13] forecast a 24.8% Level 4 AV adoption in 2040 when assuming a 5% annual price decrease as well. Instead, this study builds upon the restriction of non-SAV traffic based on geographical zones. With that, adoption rates are being steered as a consequence of private car bans while agents have the possibility to avoid SAVs by switching to alternative non-car traffic modes. Consequently, it does not describe a service based optimisation from a user's perspective in which the willingness of adoption of new technology or shared solutions are considered. This is being reflected in high waiting times and passenger hours traveled for scenarios of low levels of SAV adoption. Therefore, downsides of SAVs, such as the loss of privacy and lower service level compared to unpooled rides, are not included in our analyses. Ruch et al. [117] highlight that it is unclear if the efficiency gains of ride-pooling truly overcompensates both downsides. Additionally, technology-related travel demand changes are not incorporated, owing to the high insecurity of potential drivers in contrary directions. However, including assumptions such as the rise in travel demand in the elderly population or related to the population without access to a driver's license, would lead to different forecast dynamics.

Travel time per passengers proved to have limited impact on the final mode choice in our simulations as passenger hours spent traveling increase ranging from 27.5% to 62.1%. Considering rather time-sensitive commuting traffic, this might lead to agents not willing to adopt to SAVs on a consistent level. Hence, another fundamental limitation describes the optimization focused on total vehicle distance traveled neglecting potential increase in passenger travel times. Similarly, we see waiting time spikes for smaller SAV zones in regards to the 95% percentile of waiting times in the 6-8pm evening traffic. This indicates improvement potential, especially when serving agents that show large distances to the next operating SAVs. Considering our wide service area of SAV travel, underlines this limitation. Next to high waiting times, we observe a shift in high traffic beyond the evening peaks of 6-8pm when introducing our travel demand increase. Another limitation related to the simulation itself describes the age of travel and commuting data inputs. Based on surveys and statistics from 2009 to 2011 it has to be acknowledged that assumptions about travel behavior might be outdated. Nevertheless, related to its well calibrated and extendable nature, the MATSim Open Berlin Scenario experiences wide adopted [94, 83], resulting in improved comparability of our analysis. Due to the limited available computing power, our simulations are performed at a demand scale of 10% of total travel and two simulation iterations. However, linear up-scaling, in our case from the 10% Open Berlin Scenario, may lead to an overestimation of the Ride-hailing service levels in MATSim [85, 95]. Additionally, conducting further iterations might lead to further improvement of agent's plans. As mentioned in Section 6.2.2 another restriction of this study is that road capacity increases, derived from advanced capabilities of SAVs, have not been implemented. While efficiency increases have been considered in the final sustainability impacts, not implementing capacity level increases in an earlier processing step (such as the simulation itself) might have diminished the positive effect of SAV introduction (e.g., reducing peaks of heavy traffic). Lastly, we not incorporate additional efforts related to SAV introduction, such cleaning, repairs, or manual intervention. These challenges reduce efficiency gains and must be addressed before we can leverage the benefits of SAVs. Additionally, this study does not predict a most realistic energy mix for BEVs, it builds upon the assumption that the EU can execute on the plan of providing 100% renewable electricity sources by 2050. However, if powertrain developments can not be realized as planned, sustainability improvements might be diminished as the fundamental benefit of BEVs over ICEVs comes from the assumption of non-existing driving-related emissions.

7.2 Future Research

Based on the limitations and potential extensions of this study several directions of further research emerge.

An initial category of enhancement describes increasing the fine-granularity of our initial traffic demand forecast. By including monetary developments, social changes (e.g., remote work affecting commute traffic behavior) or regulatory interventions (such as incentivising public transport) will potentially enhance the level of detail of our forecast. Next to the demand forecast, updating the assumptions of the fundamental Open Berlin Scenario with current traffic and commuting data describes another refinement, potentially leading to higher accuracy of simulation outputs.

Further simulation-related additions include the extensive testing of higher number of iterations, using increased computational resources, in order to test the long term behavior of agents confronted with the introduced non-SAV ban areas. While minor shifts from bicycle, walking and public transport traffic modes towards the usage of SAVs have been identified, this effect might persist when running further simulation iterations. Additionally, including SAV capability such as the increase of road capacity, e.g., in the underlying road network of the simulation itself, will lead to a additional understanding of impacts of the SAV introduction to the underlying traffic behavior compared to offsetting efficiency increases in the final sustainability impact analysis. This in particular reduces findings to be derived from the introduction of efficiency increases on a simulation level. Similarly, incorporating private AVs in contrast to our SAV-based analysis will be another beneficial enhancement accounting for research that doubts car ownership to be eliminated. Other travel modes, such as electric scooters, improve the fine-granularity of future travel analyses as well.

Moreover, the transfer of our approach to various alternative cities will be crucial in order to better understand various impacts of zone-based SAV scenarios. Variations in the geographical differences, traffic behavior of cities, the network structure as well as commuter and travel behavior will potentially lead to different impacts of SAV introduction. Similarly, the influence of conducted modifications, such as introducing SAV hubs or increased seating capacities, might lead to strong variations of findings when applied to different environments. Related to modifications, other approaches of steering SAV adoption, such as cost or activity-based adoption can be used to contrast our approach of zone-based SAV introduction. Lastly, variations in the calculation of emission generations are of considerable interest as approaches fundamentally differ. Contrasting cold-start and warm start emissions instead of urban and rural traffic-based emission will lead to different perspectives on emissions and potentially different results.

8 Appendix

8.1 Overview of Relevant Papers

In the following, an overview of the papers of sustainability and forecasting related papers (see Table 8.1) as well as papers considered in the core literature review (see Table 8.2) can be found.

Nr	Source	Author	Year	Database
1	[42]	Dubey et al.	2022	Sciencedirect
2	[119]	Silva et al.	2022	Sciencedirect
3	[41]	Dlugosch et al.	2022	Sciencedirect
4	[24]	Bridgelall and Stubbing	2021	Forward & Backward Search
5	[63]	Harb et al.	2021	Sciencedirect
6	[6]	Al Turki et al.	2021	ResearchGate
7	[3]	Acheampong et al.	2021	Sciencedirect
8	[38]	Cugurullo et al.	2021	Taylor & Francis
9	[88]	Kopelias et al.	2020	Sciencedirect
10	[134]	Williams et al.	2020	ResearchGate
11	[36]	Cokyasar et al.	2020	IEEEXplore
12	[53]	Gawron et atl.	2019	Forward & Backward Search
13	[115]	Patella et al.	2019	Sciencedirect
14	[126]	Tu et al.	2019	Sciencedirect
15	[64]	Harper et al.	2018	Google Scholar
16	[113]	Pakusch et al.	2018	Forward& Backward Search
17	[68]	Hidaka and Shiga	2018	Sciencedirect
18	[13]	Bansal and Kockelmann	2017	Sciencedirect
19	[96]	Litman	2017	Forward & Backward Search
20	[108]	Moorthy et al.	2017	Forward & Backward Search
21	[32]	Chandra and Camal	2016	Sciencedirect

Table 8.1: Overview of additional sustainability and forecasting related papers considered in the literature review.

Nr	Reference	Author	Year	Database
1	[95]	Li et al.	2023	Forward & Backward Search
2	[145]	Ziemke and Bischoff	2023	Sciencedirect
3	[59]	Gurumurthy and Kockelman	2022	Forward & Backward Search
4	[17]	Ben-Dor et al.	2022	Sciencedirect
5	[14]	Baskutis et al.	2022	Sciencedirect
6	[92]	Lecureux and Kaddoura	2021	Sciencedirect
7	[144]	Yefang et al.	2021	ProQuest
8	[118]	Schweizer et al.	2021	ProQuest
9	[69]	Hogeveeen et al.	2021	ProQuest
10	[94]	Li et al.	2021	Sciencedirect
11	[34]	Chouaki and Puchinger	2021	Sciencedirect
12	[114]	Parsa et al.	2021	Taylor & Francis
13	[147]	Zwick et al.	2021	Sciencedirect
14	[109]	Nahmias-Biran et al.	2021	Forward & Backward Search
15	[39]	Dai et al.	2021	Sciencedirect
16	[85]	Kaddoura and Schlenther	2021	Sciencedirect
17	[140]	Zhikang et al.	2020	ProQuest
18	[83]	Jing et al.	2020	IEEE
19	[1]	Abdulsattar et al.	2020	Google scholar
20	[7]	Alisoltani et al.	2020	Springerlink
21	[111]	Oh et al.	2020	Sciencedirect
22	[97]	Liu et al.	2020	Taylor & Francis
23	[5]	Maghraoui et al.	2020	Forward & Backward Search
24	[82]	Javanshour et al.	2019	Taylor & Francis
25	[130]	Vosooghi et al.	2019	Forward & Backward Search
26	[146]	Ziemke et al.	2019	Sciencedirect
27	[99]	Liu et al.	2018	Google scholar
28	[74]	Hyland and Mahmassani	2018	Forward & Backward Search
29	[70]	Hörl	2017	Sciencedirect
30	[104]	Martinez and Viegas	2017	Sciencedirect
31	[98]	Liu et al.	2017	Springerlink
32	[81]	Jaeger et al.	2017	IEEE
33	[67]	Heilig et al.	2017	Forward & Backward Search
34	[57]	Gora and Rueb	2016	Forward & Backward Search
35	[20]	Bischoff and Maciejewski	2016	Sciencedirect
36	[22]	Boesch and Ciari	2015	IEEE
37	[141]	Zhang et al	2015	Sciencedirect
38	[142]	Zhang et al.	2015	Forward & Backward Search
39	[45]	Fagnant et al.	2014	Sciencedirect

Table 8.2: Overview of relevant papers considered in the literature review.

8.2 Calculations for the Moderate Traffic Demand Forecast

Table 8.2 shows underlying calculations for the moderated traffic demand forecast, according to Chapter 6.1.

Age Group	2011 [122]	2030 [123]	2050 [123]	Change 2011-2050	Age Factor	Population Share	Overall Travel Impact 2011-2050
18-19	87	129	127	45.2%	0.74	1.8%	0.5%
20-29	756	695	724	-4.3%	1.18	15.4%	-0.7%
30-39	731	858	844	15.5%	1.28	14.9%	2.5%
40-49	966	1,000	838	-13.2%	1.31	19.6%	-2.9%
50-59	859	764	874	1.7%	1.28	17.5%	0.3%
60-69	660	878	918	39.1%	0.92	13.4%	4.1%
70-79	595	648	611	2.6%	0.64	12.1%	0.2%
80+	262	341	504	92.0%	0.36	5.3%	1.5%
Total	4,916	5,313	5,438	10.6%	-	100.0%	6.6%

Table 8.3: Traffic demand derivation assuming moderate population growth per age group across Berlin and Brandenburg.

8.3 Extensive simulation run using the 1% Open Berlin Scenario

Figure 8.1, 8.2, 8.3, and 8.4 are outputs of an exemplary test run which dynamically introduces SAVs to the 1% Open Berlin Scenario. This means the travel mode is introduced without steering demand, such as through regulatory interventions. We can examine changes in the first 22 iterations, while key figures such as overall numbers of passenger hours traveled and passenger kilometers stay comparatively consistent. Related to the bottom up introduction of SAVs, the first 22 iterations show the highest changes on SAV distance travelled.

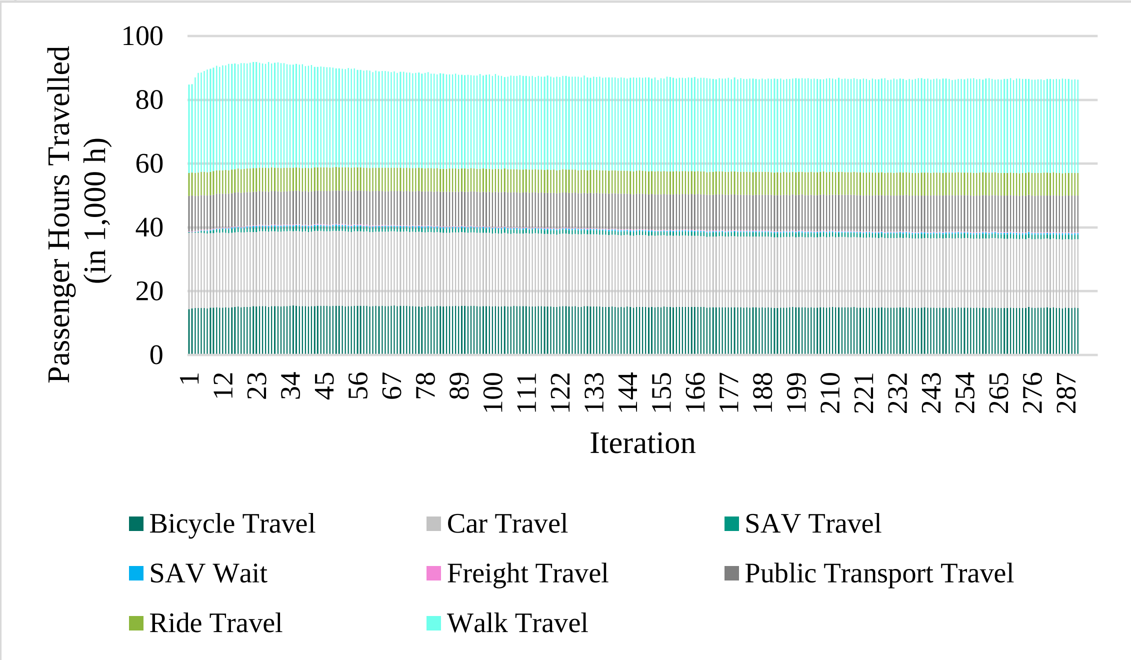


Figure 8.1: Passenger hours traveled per traffic type across 290 iterations, graphic adapted from the output files of the Open Berlin Scenario [146].

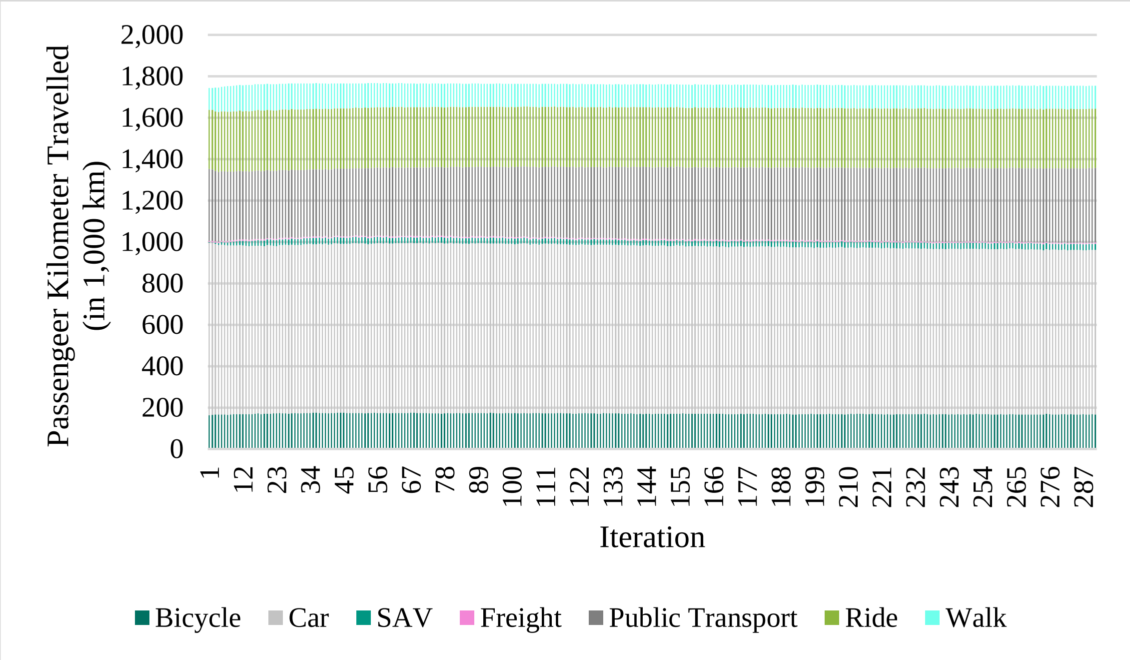


Figure 8.2: Passenger kilometer traveled per traffic type across 290 iterations, graphic adapted from the output files of the Open Berlin Scenario [146].

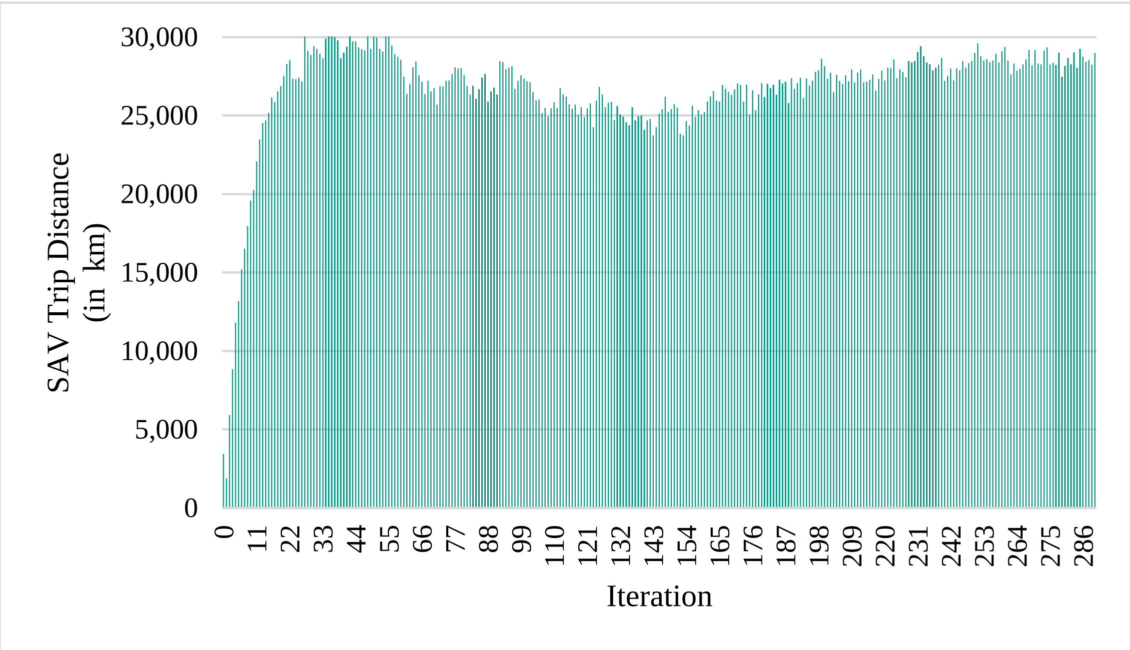


Figure 8.3: SAV passenger kilometer traveled per traffic type across 290 iterations, graphic adapted from the output files of the Open Berlin Scenario [146].

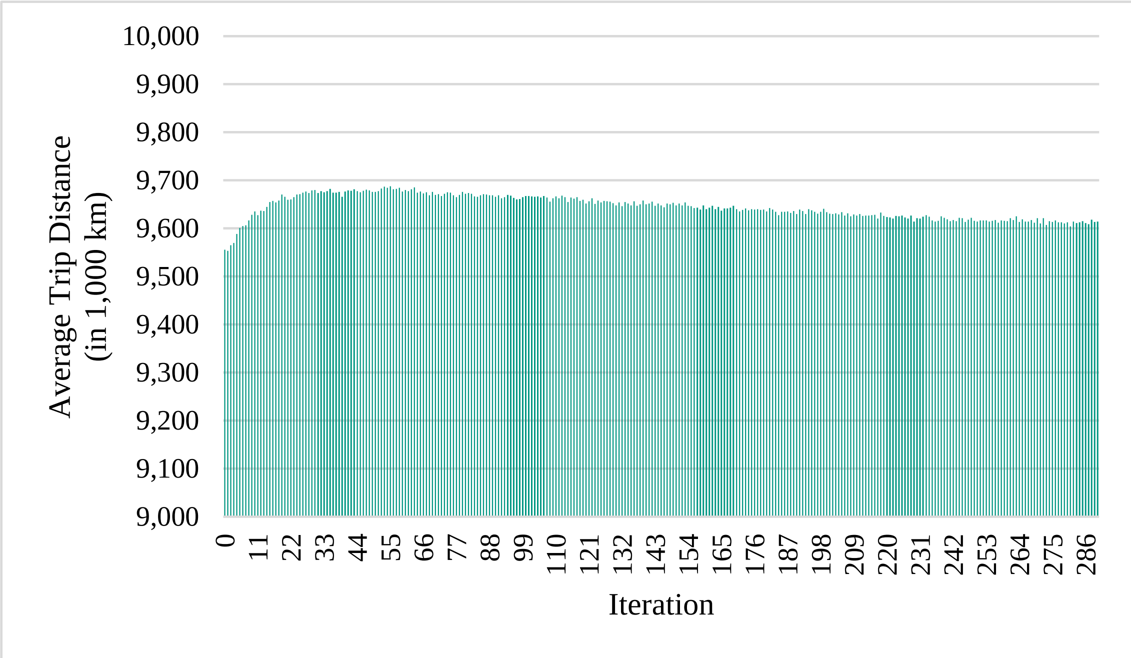
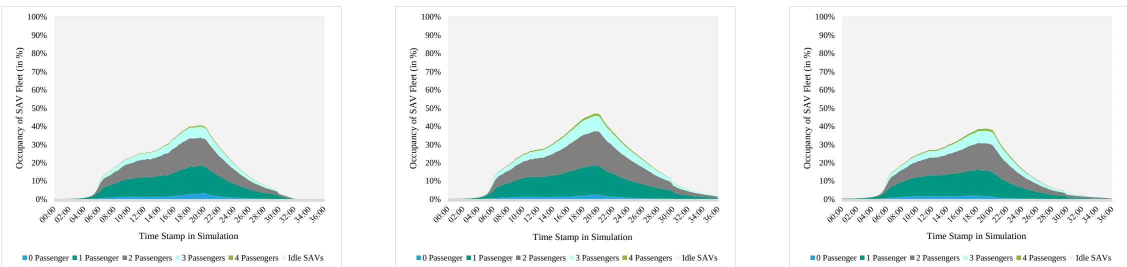


Figure 8.4: Average trips distance all travel modes combined across 290 iterations, graphic adapted from the output files of the Open Berlin Scenario [146].

8.4 Additional Visualisations for the Scenario Results

Figure 8.5 shows the vehicle occupancy comparing SC1.1, SC1.2 and SC1.3.



(a) SC1.1.

(b) SC1.2.

(c) SC1.3.

Figure 8.5: Vehicle occupancy of SAV fleet across the three scales of SAV introduction, graphic adapted from the output files of the Open Berlin Scenario [146].

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