Coordinating Charging Behavior

Engineering Systems for Electric Vehicle Users

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For my grandpa

Ludwig Horn
(1936-2017)

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List of Abbreviations

AC	Alternating Current
AUC	Area Under the Curve
AV	Autonomous Vehicle
AVP	Automated Valet Parking
AVPS	Automated Valet Parking Service
CP	Constraint Programming
CPO	Charge Point Operator
DC	Direct Current
DSS	Decision Support System
EDL	Early Departure Loss
EMP	Electric Mobility Provider
EV	Electric Vehicle
FCFS	First-Come-First-Served
FJSP	Flexible Job-Shop Problem
GHG	Greenhouse Gases
HEV	Hybrid Electric Vehicle
ICEV	Internal Combustion Engine Vehicle
JSP	Job-Shop Problem
KBA	Kraftfahrt Bundesamt (Federal Office for Motor Traffic)
KPI	Key Performance Indicator
MCDM	Mulit-Criteria Decision-Making
OFJSP	Online Flexible Job-Shop Problem
OL	Occupancy Loss
OSSP	Open-Shop Scheduling Problem
PHEV	Plug-in Hybrid Electric Vehicle
POI	Point of Interest
PV	Photovoltaic
RES	Renewable Energy Sources
SoC	State of Charge
TALC	Technology Adoption Life Cycle
V2G	Vehicle-to-Grid
V2H	Vehicle-to-Home

Part I.

Fundamentals

Chapter 1.

Introduction

Climate change is a complex challenge that requires broad societal actions. Various sectors contribute to greenhouse gas emissions and have to be transitioned to a climate neutral operation. Among those, transportation is one of the sectors that has been struggling the most. Within the transportation sector, electric vehicles have the potential to reduce greenhouse gas emissions substantially (IEA, 2019). However, the transition to electric mobility might require users to adapt their mobility patterns to the technical limitations of the vehicle. Even though innovators and early adopters are eager to change their behavior for the benefit of driving an electric vehicle, the mainstream market, as defined in the Technology Adoption Life Cycle Model (Beal and Bohlen, 1956), might be more unwilling to adjust in order to adapt to technological innovations such as electric vehicles. This creates a chasm between the customers in the early and mainstream market, which has the potential to diminish the environmental contribution of electric vehicles. To cross this chasm, the eco-system of electro-mobility needs to be developed in a way, that makes a switch to electric vehicles behaviorally compatible for users (Gourville, 2005). Even though research has focused on the development of charging strategies (Flath et al., 2012) and expansion of charging infrastructure (Pagany et al., 2018), user behavior has not yet been adequately addressed. This dissertation closes this gap by focusing on empirical mobility behavior and by developing and evaluating corresponding strategies for the transition to electric mobility. To include user behavior, empirical data from both electric but also internal combustion engine vehicles is used, as an exclusive focus on early adopters of electric vehicles can induce a sample bias (Rezvani et al., 2015). It is of utmost importance to introduce new approaches to coordinate charging behavior based on the users' current mobility patterns. To achieve this goal, the dissertation differentiates between private and public charging behavior as well as between residential and commercial customers. This differentiation describes a two-by-two matrix. Moreover, based on the results of the presented analysis, autonomous parking is considered to further improve the behavioral compatibility of electric mobility. In conclusion, this dissertation supports academics in the modelling of user behavior for electric mobility and provides management insights for the implementation of charging infrastructure and strategies to transition electric mobility into the mainstream market.

1.1. Motivation

Reducing greenhouse gas emissions in order to diminish the effects of climate change is one of the biggest challenges of today's societies. To achieve this essential goal, 197 countries signed the Paris Agreement in 2015 and pledged to decrease their emissions to comply with the ambition of limiting global climate change to well below 2°C. Germany, as an example, aimed to reduce its greenhouse gas (GHG) emissions by at least 55% until 2030 compared to the year 1990 (Heinrichs and Markewitz, 2017). In order to accomplish the targets of the Paris Agreement, the German Environmental Agency differentiates between six sectors, including the energy, industry, building, transportation, agriculture and waste sector. While the emissions were reduced, for example, by 45% in the energy and 34% in the industry sector, the transportation sector remains the only sector without a substantial reduction. Lately, the achieved reduction was still less than 1% when compared to 1990 (UNFCCC, 2021). Further, due to advancing population growth and urbanization, the demand for transportation will increase even further (Khalili et al., 2019). As a consequence, there is a strong need to decarbonize the transportation sector. This can be achieved, for example, through improved energy efficiency of vehicles sold. However, there is evidence that the currently predominant technology of combustion engines vehicles (ICEV) cannot fulfill the targets for 2030 (Miotti et al., 2016) and consequently new propulsion systems need to be implemented.

In order to cope with the increasing transportation demand while reducing GHG emissions, electric mobility has proven to be a powerful technology (Longo et al., 2016; Razeghi and Samuelsen, 2016) and is extensively discussed in current literature as well as in politics. Electric vehicles (EVs) play an elementary role in the electric mobility ecosystem and shift carbon emissions from the tail pipe to the electricity sector and can thus profit from renewable energy sources (RES) installed in recent years. Globally, EVs contribute to a reduction in GHG if the carbon intensity of the generation mix is low (IEA, 2019). However, EVs even eject fewer CO_2 equivalents than diesel vehicles in scenarios with high electricity generation emission factors (Moro and Lonza, 2018; Falcão et al., 2017). Moreover, the advantages of EVs are not limited to lowering GHG emissions. Research shows that EVs have the potential to reduce numerous pollutants, including nitrogen oxide and particulate matter (Tsakalidis et al., 2020; Donateo et al., 2015) as well as to reduce noise disturbances (Loehmann et al., 2014), creating a strong need for a rapid EV adoption.

As a consequence, new regulations and incentives to foster EV adoption have been introduced in recent years. In Germany, as an example, financial premiums of up to 9,500€ when purchasing an EV (Mönnig et al., 2020) as well as a suspended vehicle tax for 10 years (Tietge et al., 2016) have been offered. However, these financial incentives cannot compensate the technical limitations of EVs for all customers, since especially limited access to charging infrastructure is still a barrier for EV adoption (Zhang et al., 2018). This lack of adequate charging stations can create a skepticism towards EVs due to fear of running out of range, also known as range anxiety (Neubauer and Wood, 2014), and the concern of not being able to maintain the current mobility pattern.

This skepticism can be further broken down using the technology adoption life cycle (TALC) introduced by Beal and Bohlen (1956). According to the TALC, the success of an innovation depends on two factors, which are the *Degree of Behavior Change Required* and the *Degree of Innovation* (Gourville, 2005). Whereas the latter fosters the adoption of an innovation, increasing the *Degree of Behavior Change Required* leads to skepticism and should therefore be minimized. EVs are affected by theses two factors as they are perceived as innovative but require users to adapt to the technical limitations of the vehicle. Most innovations follow this characteristic, which is also referred to the *long haul* (Mogull, 2021). Furthermore, the adoption of highly innovative products is often linked to a trade-off between loosing an existing benefit and exchanging it with another greater benefit. With EVs, adopters, for example, lose the benefit of easy refueling but gain an environmentally friendly mode of transportation (Gourville, 2005). The result of this trade-off is different for every customer and consequently requires a further categorization of potential users to determine the extent of their skepticism and the concerns that need to be addressed. This categorization can be achieved using the TALC, where users are classified according to their willingness to accept an innovation starting from the innovators and expanding towards the laggards.

The first two user groups within the TALC are the innovators and early adopters, who are also referred to as the early market. These customers are prone to developing their own solutions in order to use the product successfully and accept an inherent greater risk associated with being the first to try a new technology (Mogull, 2021). For EV adoption, this suggests that innovators and early adopters are willing to cope with the limitations of EVs, as long as one of their objectives is improved, such as environmental friendliness (Plötz et al., 2014b) or the experienced joy while driving the vehicle (Frenzel et al., 2015). In total, the early market is estimated to represent a total of 16% of the market share (Mogull, 2021). What follows is considered the mainstream market, consisting of the early majority, late majority and laggards, whose customers are more cautious and resistant to adopting new technologies and to changing their behavior (Mogull, 2021). It is especially within the mainstream market, where skepticism towards EVs can be observed.

This shift from early market to mainstream market is a crucial decision point within the acceptance of a new innovation and is referred to as the *chasm*. The chasm describes a period where the early market is still trying to digest the changes of an innovation and the mainstream market waits to see if anything good will come out of it (Moore and McKenna, 1991). This is a critical phase for an innovation and insufficient actions to overcome the chasm can inhibit its success. Due to the important contribution of EVs towards reducing GHG emissions, it is of utmost importance for this innovation to cross the chasm and establish itself as the dominant propulsion system within vehicles. Consequently, there is a need to develop solutions that help EVs to gain higher acceptance within the population, which is in the focus of this dissertation. Research suggests multiple strategies for an innovation to cross the chasm, which depend on the innovativeness of a product a product is and to what extent users need to change their behavior. For EVs and other innovations within the *long haul*, Gourville (2005) describes the strategy to *make it behaviorally compatible* as a promising option to counter the chasm by proactively reducing the required behavior change by users to adopt an innovation.

With a market share of 17% of new car registration in Germany in 2021, EVs are currently expanding into the early majority, and hence, need to address the challenges linked to this mainstream market. Following the findings of Gourville (2005), there is a strong need to design and improve the EV ecosystem to counter the chasm. With the removal of easy refueling, users require solutions to charge their vehicles in a way that is compatible with their current mobility patterns. Due to the important potential of EVs towards reducing GHG emissions, the main objective of this dissertation is to provide novel approaches for EV charging that consider user behavior. This will allow new users of EVs to switch to electric mobility without a change in their current behavior and hence help in overcoming the chasm and fostering EV adoption.

In pursuance of this goal, this thesis focuses on users and their charging strategies that are compatible with the users' mobility patterns. There is no universal charging strategy that provides the best solution for users under all circumstances. Therefore, it is necessary to address different use cases and develop charging strategies tailored to the individual user and their associated mobility pattern. In order to develop such charging strategies, first, a better and more detailed understanding of who these users are and what kind of mobility behavior they have is needed. This detailed view on both users and mobility behavior is achieved through partitioning them into two separate categories, both with their own individual challenges and opportunities.

Users can be categorized using the governmental definition. When looking at the new vehicle registration in Germany, the Federal Office for Motor Traffic (KBA) distinguishes between two clusters of users, which are private and commercial vehicle owners. While the first account for 38% of new vehicle registrations in 2020, the latter represent 62% (KBA, 2021). Both user groups have their own individual mobility patterns that need to be taken into account. For private vehicle owners, driving to work and shopping are the most common types of travel (Flores et al., 2016), where commuting accounts for almost half of the total distance traveled (Nobis and Kuhnimhof, 2018). In comparison, commercial vehicles are characterized by a higher distance traveled (Paffumi et al., 2018) and might often have a more predictable mobility pattern (Detzler, 2016). Due to these dissimilarities, the needs and requirements of both user groups need to be addressed individually to cross the chasm.

Similar to the differences in users, the charging behavior can also be differentiated into charging sessions at private and public charging infrastructure. This is a result of using electricity as a fuel, which is available at private locations, whereas refueling an ICEV is only possible at public fuel stations. The wide availability of electricity is a big advantage for developing charging strategies and thus, it is primarily a question of making it available for EVs rather than providing a new supply infrastructure. This offers completely new solutions to make EVs behaviorally compatible, as charging sessions could be distributed at multiple locations along the mobility pattern. While users within the mainstream market might fear long charging times, the ability to operate and charge using their own charging infrastructure might help to overcome the chasm. For EVs of private owners, this could translate into charging at home and for commercial fleets charging at the company depot. Both charging at public and private charging infrastructure comes with its own advantages and disadvantages that need to be considered separately. The two different categories of users and the two different charging behavior possibilities lead to four different cases, where user behavior needs to be addressed. In every one of the four use cases, the focus is on the individual needs of the EV users and solutions that make the switch from ICEVs to EVs *behaviorally compatible*. These four quadrants are illustrated in Figure 1.1.

The main focus of this thesis is to cross the chasm in the life cycle of EVs. Consequently, the technical solutions for charging an EV used in this thesis are derived from technologies available today. However, the market is still developing and new solutions are currently being investigated that might help to overcome limitations of today's charging stations, especially the ones that are linked to user behavior. One limitation found across the four cases shown in Figure 1.1 is that users are not willing to move their vehicle after a charging session is completed (Philipsen et al., 2016), which has a negative impact on both other EV users as well as charging station operators. With technological progress in vehicle automation, this negative impact can be addressed as users do not need to take action anymore to clear a charging station. Based on the findings of the four use cases, this thesis also broadens its scope on the potential of autonomous vehicles (AV) and their ability to relocate within a car park.

Overall, this thesis provides novel solutions to tailor charging strategies for individual customer groups and user behavior that allow a seamless transition from an ICEV to an EV without the need to change the current mobility pattern. The findings can be used to overcome the chasm between the early and mainstream market and help to foster EV adoption.

Charging Station / EV Owner	Limited Access	Public
Private		
Commercial		

Figure 1.1.: Matrix

1.2. Research Questions

The integration of user behavior into charging strategies has to be addressed individually for different use cases. To achieve this goal, the research outline of this thesis follows the two dimensions introduced in Figure 1.1. First, private and public charging solutions for private EV owners are introduced and analyzed. Then, the focus is shifted towards commercial EV owners and their unique challenges to switch to EVs with a minimal impact on their operation. Finally, these findings are transferred to a future use case, where vehicles are capable of parking autonomously.

Charging at home is an easy and comfortable approach to integrate charging into the current mobility pattern of private EV owners, as there is no need for additional trips and private parking locations are the locations with the longest parking duration (Huber et al., 2019). As a consequence, the dwell time typically exceeds the time needed for charging. Nevertheless, this type of charging requires an investment into adequate charging equipment, for example, a wallbox and a private parking spot with an available power grid connection. Especially in densely populated areas, the latter might not be achievable, leading to the question if there are possible other solutions to provide the comfort of home charging without the need for a charging station at each parking lot. In this case, sharing of existing infrastructure can provide benefits both to the investor and operator as well as to other neighboring EV owners. In order to allow for a comfortable charging experience, EV users sharing a wallbox should have compatible mobility patterns, meaning that their need for charging should not temporally overlap. To achieve this, a two step approach is pursued. First, clusters of users with similar mobility patterns are identified. In a second step, these clusters are then matched to create groups of private EV owners that can share a wallbox while not experiencing any impact on their mobility pattern. Consequently, the first research question refers to quantifying the share of private EV owners that can use a wallbox as a collective.

Research Question 1 *How many private EV owners can share a home charging station without a negative impact on their mobility pattern?*

In order to provide the same mobility as with an ICEV, home charging can be supplemented with public charging stations available within cities as well as along highways. Whereas fast charging at highways provides little flexibility to the EV owner and follows a similar process as refueling an ICEV, public charging within cities allows EV users to charge at the destination of their trips. This is referred to as *public destination charging* and describes the charging of EVs in places where parking is independent of the State of Charge (SoC) of the vehicle (Schmidt et al., 2020). It has a great potential as it does not force users to change their mobility behavior at all and is also available for EV owners without access to a private charging station. However, due to the charging time of EVs and the limited time spent at the destination, not every location has the same potential to deliver electricity to the customer. This has an impact on both the recharged range of private EV owners as well as on the economic evaluation of the charging station operator. As a consequence, there is a need to identify locations where the mobility pattern of EV owners provides benefits to both users as well as charging station operators.

Research Question 2 *What is the impact of parking behavior on a successful public charging session at a destination charging location?*

While private EVs are an important cornerstone of sustainable individual mobility, commercial uptake has the potential to greatly increase the pace of EV adoption.

However, commercial fleet electrification comes with particular challenges and characteristics that require distinctive charging strategies. Many commercial vehicle fleets are not continuously in operation and have a central location from which they start their trips, such as the company's headquarter or a depot. Similar to home charging for private EV owners, charging at such a central location provides a comfortable possibility to include charging sessions within the current mobility pattern without the need for additional trips. In addition, companies have the possibility to scale the installed charging infrastructure to address their individual needs and design rules on how the infrastructure should be used. This combination of charging infrastructure and charging strategy determines when a vehicle will be available for the next trip and consequently sets the boundaries for fleet operation. The fear of possible mobility constraints has diminished the intention to adopt EVs in commercial fleets (Globisch et al., 2018). In order to overcome this fear and hence to allow for fast EV adoption, there is a need to identify commercial fleets that have a user behavior that is well suited for private charging and to provide decision support for a charging strategy to allow a successful operation of the charging infrastructure. This is addressed in the following research question.

Research Question 3 *Under which conditions are commercial fleets suited for electrification considering the technical limitations of the vehicles and charging infrastructure?*

Nevertheless, not every commercial fleet is operated from a depot and might face uncertainty with regards to the actual trips and especially the distance traveled on the subsequent day. As a consequence, there is a need to charge at public charging stations to provide sufficient range throughout the day. Taxis, as an example, do not know their assignments in advance and have to react based on customer demand. From an ecological point of view, taxis have a great potential to reduce GHG emissions due to their high mileage (Gao and Kitirattragarn, 2008) and should therefore be prioritized. Taxis operate profit based, and therefore, adopting an EV should not reduce the earnings. To analyze the impact of electrification for taxis from an economical point of view, this thesis follows an empirical approach using recorded trips within the city of Chicago. Based on the provided data of individual taxi mobility patterns, charging strategies are developed and their impact on earnings are quantified. The analyzed charging strategies can be categorized into basic and advanced strategies. Whereas the prior focuses on a combination of private and public charging stations that are visited once the battery is depleted, the latter quantifies the impact of foresight on future demand as well as a potential charging station expansion at frequently visited locations. This economic evaluation of charging strategies is investigated with the fourth research question.

Research Question 4 *Under which conditions can individual taxis be electrified following an economical evaluation of empirical taxi data?*

One main finding of this thesis is that in order to fulfill customer needs and to allow an efficient operation of charging infrastructure, the time during which vehicles block charging stations has to be minimized. For customers, this reduces the risk of not being able to charge on arrival and for charging station operators, the time in which the infrastructure is generating revenue is maximized. There are several solutions to address this issue, such as an additional fee for blocking a charging station or mobile charging stations that can be moved between vehicles. The innovation of autonomous driving might be another solution to solving this issue. Automated Valet Parking (AVP) is considered one of the first use cases for autonomous driving (Banzhaf et al., 2017) and describes a situation where vehicles can park themselves in designated areas. This provides a great benefit for EV owners as in addition to a comfortable parking experience, vehicles can also be charged. Further, autonomous driving might also provide benefits to charging station operators as it removes the need for customer intervention to clear a blocked charging station. From a car park operator's perspective, this enables a completely new variety of additional services that can be provided to customers. Besides the service *parking* and *charging*, car park operators might allow their customers to get their vehicles washed, repaired or to accept deliveries. This creates a platform where car park operators have to schedule services within the limitations given by the dwell time of customers. However, it is unclear how such a platform should be operated in order to utilize the flexibility provided by its users while maximizing the demand of customers covered. Research Question 5 considers such an operation for the AVP use case.

Research Question 5 *By how much can automated valet parking increase the utilization of charging and parking lot service infrastructure in an online operation?*

These five research questions are answered within this thesis and provide new insights on charging strategies that are engineered upon user behavior and that enable an easy transition from ICEVs to EVs. In the following, the structure of the thesis is presented.

1.3. Thesis Structure

The outline of this dissertation follows the two dimensions introduced in Figure 1.1, which are the user type of an EV and the charging behavior and the research questions presented in the previous section. It is divided into five parts.

Part I introduces and motivates the need for charging solutions that focus on user behavior. It highlights the urgency to foster EV adoption from an ecological point of view and identifies potential barriers for such an innovation using the TALC. In Chapter 2, foundations of individual electric mobility are presented, with a focus on the technical properties of EVs, the options of available charging infrastructure and the characteristics and requirements of EV users. Part II provides research on charging strategies for private EV users. In Chapter 3, the mobility patterns of EV users are analyzed and a quantitative analysis of the possibility for sharing private charging stations at home is provided. Chapter 4 elaborates on possible public locations for destination charging and identifies sites with a large potential to provide electricity to EV users and consequently to provide revenue for the charging station operator. Part III examines possibilities to electrify commercial fleets. In Chapter 5, a decision support tool is introduced that allows fleet managers to identify the potential for fleet electrification with charging infrastructure at the company depot, while considering the charging strategy and foresight. Chapter 6 provides insight into charging strategies at public charging infrastructure for electric taxis and introduces possible extensions to counter lost revenue due to charging. In Part IV, an outlook on future possibilities for EV charging is provided. Using AVP, Chapter 7 analyzes the potential of autonomous driving for parking lot operators and the possibility to provide charging and other services. Finally, Part V provides a conclusion that summarizes the key contributions of this thesis and presents an outlook for further research in Chapter 8. [1]

Part I Fundamentals	**Chapter 1** Introduction	**Chapter 2** Foundations of Individual Electric Mobility
Part II Charging Private Electric Vehicles	**Chapter 3** Sharing of Private Charging Stations at Home	**Chapter 4** User Behavior for Destination Charging
Part III Charging Commercial Electric Vehicles	**Chapter 5** Decision Support for Charging Electric Fleets	**Chapter 6** Public Charging of Electric Taxis
Part IV Automated Charging	**Chapter 7** Scheduling Services for Automated Valet Parking	
Part V Finale	**Chapter 8** Conclusion	

Figure 1.2.: Thesis Structure

[1] Chapters 3 to 5 as well as Chapter 7 rely on or fully comprise published articles or articles currently under review. In every case, I disclaim this clearly at the beginning of the respective chapters. Since I collaborated with fellow researchers for these articles, I consistently refer to the authors as “we” throughout these chapters. Where appropriate, figures, tables, algorithms, and appendices were reformatted, and captions were updated. The numbering of the chapters and sections and all references were adjusted to the thesis structure.

Chapter 2.

Foundations of Individual Electric Mobility

Even though the share of public transport users and cyclists increased in recent years, motorized individual mobility still accounts for more than half of the distance traveled by individuals (Nobis and Kuhnimhof, 2018). Traveling by car provides flexibility to both private and commercial vehicle users as traveling times are not bound to a fixed schedule and it is therefore the most popular mode of transportation. Nevertheless, drivers still have to consider the characteristics of the vehicle, such as the range but also the existing infrastructure such as parking lots and refueling stations in order to utilize the advantages of individual mobility.

With the shift towards EVs, these characteristics of individual mobility change and EV users have to adapt to benefit from this new technology. To engineer charging strategies that allow a seamless transition from ICEVs to EVs, it is essential to understand the fundamentals of the new vehicles and infrastructure from a technical perspective to fully utilize their potential. Besides the change in technology, it is also important to understand who the users of EVs are as well as their needs and the challenges they encounter when adopting an EV. These aspects will be addressed in the following chapter to allow for a well-grounded analysis of the five research questions of this thesis.

2.1. Technical Properties of Electric Vehicles

Within this section, the term *Electric Vehicle (EV)* is introduced from a technical perspective. The technical properties of EVs deviate from those of ICEVs and are responsible for both the potential as well as the obstacles that need to be addressed by charging infrastructure and charging strategies.

2.1.1. Types of Electric Vehicles

An EV is a means of transportation with one or more electric motors that is powered by an off- or on-vehicle electricity source. While this definition includes electric ships, trains, planes and other modes of transportation, the focus of this dissertation lies on ground based vehicles participating in today's street mobility.

There are different types of vehicles that differ in their degree of electrification (Liao et al., 2017). Vehicles with an internal combustion engine (ICE) dominate the vehicle population in operation on the road. ICEVs do not have an electric traction motor and hence are not considered EVs. The first category of vehicles utilizing an electric motor are hybrid electric vehicles (HEV). HEVs have a battery that is capable to store energy generated during the breaking processes, also referred to as recuperation. Here, the electric motor acts as a generator and is capable to provide an extra boost for the next acceleration. The second category are the plug-in EVs, which include both hybrid technologies as well as fully electric vehicles. The main difference to HEVs is that the energy stored in the battery is no longer limited to recuperation, but it can also be charged from an external power source. Plug-in Hybrid Electric vehicles (PHEV) have the ability to drive short distances using the energy from the battery but rely on a second energy source for longer trips. This can be an ICE but also a Fuel-Cell, for example. Fully electric vehicles on the other hand solely rely on electricity provided by the internal battery.

The focus of this dissertation is on fully electric road vehicles, due to the follwing two reasons. First, fully electric vehicles have a high potential to reduce GHG and also provide other benefits, such as noise reduction. Second, fully electric vehicles have their own unique challenges and opportunities. Whereas HEV and PHEV can be used the same way as an ICEV, fully electric vehicles require a change in behavior due to their limited range and longer charging times. In this thesis, the term electric

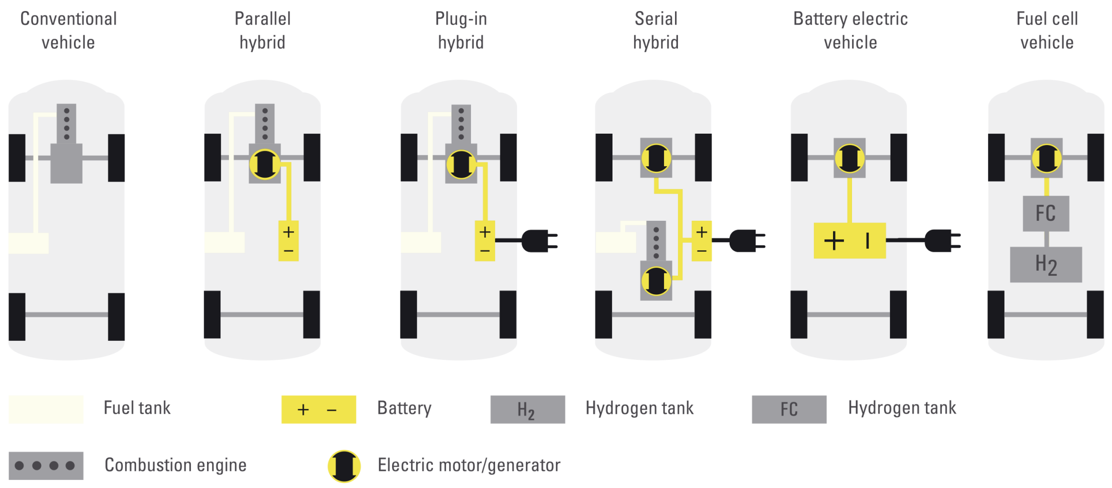

Figure 2.1.: Differentiation of Drive Trains with increased Electrification (e-mobil BW, 2011)

vehicles (EV) is used to describe a fully (battery) electric vehicle.

2.1.2. Advantages and Disadvantages

Due to the change in the drivetrain, the inclusion of a battery and the possibility to interact with the electricity grid, owners of EVs experience changes in the way they use their vehicle. In this section, the advantages and disadvantages associated with the characteristics of EVs are discussed.

Advantages The main function of a vehicle is to transport people and goods to different locations. Here, one noticeable change of EVs compared to ICEVs is the difference in driving characteristics, such as noise and driving distance. The motors within EVs have a higher torque even at low motor rotation frequency, which is perceived as dynamic driving and allows for faster acceleration (Plötz et al., 2014b). In addition, electric motors emit lower noise leading to a quieter ride (Loehmann et al., 2014). As a consequence, driving pleasure is one of the central reasons for EV adoption (Frenzel et al., 2015).

Besides driving characteristics, the purchase of an EV also impacts the cash flow associated with vehicle ownership. EVs typically have higher initial costs that are compensated by lower operational costs. On a per kilometer basis, the energy required to drive EVs is less expensive than gas for an ICEV at current prices (Laurischkat et al., 2016; Frenzel et al., 2015), which makes EVs the better investment considering the total cost of ownership if the driving distance is correspondingly high. Besides electricity costs, several countries provide benefits, such as an exemption from purchase and value-added tax in Norway (Bjerkan et al., 2016) or suspended vehicle tax for 10 years in Germany (Tietge et al., 2016). These policies help to make EVs more economical. In some scenarios, vehicle owners can even save money when exchanging their ICEV for an EV.

Besides economical benefits, EVs can also provide ecological benefits. Research shows that a shift towards EVs contributes to the deployment of additional wind and solar power generation (Loisel et al., 2014) and hence, advances the reduction in GHG (Hanemann et al., 2017; IEA, 2019). Besides CO_2, EVs also have the potential to reduce other pollutants, such as nitrogen oxide and particulate matter (Donateo et al., 2015; Razeghi and Samuelsen, 2016; Ferrero et al., 2016). They therefore provide benefits for the environment in general but also increase the air quality within cities. Overall, CO_2 emissions of EVs are 4.6 times lower compared to a diesel powered vehicle (Falcão et al., 2017) and could save up to 50-60% of GHG emissions in the EU (Moro and Lonza, 2018). As a consequence, EVs are considered one of the most promising solutions to address climate change and when combined with RES provide a great opportunity for the environment (Longo et al., 2016).

The advantages of EVs are not limited to individual vehicle owners but also extend to commercial fleets. Consequently, fleet managers have fostered EV adoption to benefit from their advantages, such as their potential to reduce cost, creating a positive image of the company while reducing emissions (Plötz et al., 2014b; Freitag et al., 2017). Furthermore, even besides their benefits in operation, EVs can be used by fleet managers to generate revenue even outside of business hours, such as by providing ancillary services (Hu et al., 2013). In addition, electric fleets can profit from on-site photovoltaic generation when charging EVs at the company's location (Seddig et al., 2017).

While charging, EVs interact with the power grid and have the potential to provide advantages to different participants within the power system. This is due to the fact that vehicles are in general parked for 95% of the day (Noel et al., 2019a). As a consequence, the dwell time at a location exceeds the charging time leading to time flexibility while charging. (Huber and Weinhardt, 2018) show that utilizing this flexibility and shifting charging sessions to times with higher RES in the energy mix has the potential to reduce CO_2 emissions in Germany. The concept of scheduling charging sessions to comply with different goals is called *smart charging* and is further elaborated in Section 2.2.3. Smart Charging demonstrates, that the advantages of EVs are not limited to EV owners but extent to others such as grid operators and energy providers. However, despite these numerous benefits, the adoption of EVs is also associated with several disadvantages that are addressed in the following.

Disadvantages Even though EVs provide benefits to their users and the environment, their adoption is limited by the fact that their lower pollution levels are not directly internalized in their price (Sierzchula et al., 2014). Especially in logistic companies, the high investment costs for EVs, mainly due to the battery price, can be a barrier to prevent such fleets from purchasing EVs (Freitag et al., 2017). When looking purely at costs, Sierzchula et al. (2014) shows that most fleet managers were discouraged from buying additional EVs until investment prices decrease substantially.

But also from an operational point of view, EVs have limitations that require users to actively adapt to. Flores et al. (2016) identify three main disadvantages when using EVs, which are limited range, slow charging and reduced availability of charging infrastructure. Due to the weight and volume of batteries, EV producers are restricted by the energy capacity they can fit within the vehicle leading to a decreased driving range when compared to an ICEV. Especially in the context of EV adoption, limited range has been identified as on of the main barriers for customers to choose an EV (Liao et al., 2017; Franke et al., 2012; Herrmann et al., 2018). This challenge is magnified by the longer time needed to charge an EV. Whereas refueling an ICEV only takes several minutes, charging an EV can take several hours. Even though there are solutions to fast charge an EV, the charging process is still slower than refueling and it can have a negative impact on battery degradation (Yang et al., 2018). To address this limitation, a wide network of charging stations is needed to allow users to charge their vehicle whenever they park instead of having to toake an additional trip to charge. Especially for commercial fleets, a wide network of public charging station or the possibility to charge at the company base is crucial, as fleet managers fear a negative impact on operation due to queues at charging stations (Morganti and Browne, 2018). To gain a better understanding of how EVs are charged and what kind of technical possibilities exist, the next chapter focuses on charging infrastructure.

2.2. Charging Infrastructure

One of the main advantages of shifting towards EVs is that electricity already is a major part of our society and the corresponding infrastructure is established. Rather than creating a new distribution network, the challenge of charging EVs is a question of creating solutions to link EVs to an already existing power grid. To achieve this, several technical implementations exist. Within this section, first, an overview on available charging infrastructure and modes of charging is provided. This overview defines the composition of technical solutions available to develop approaches that integrate user behavior. Second, a summary of possible locations for charging infrastructure and different challenges is provided and the potential connected to specific sites are discussed. The section is completed with an overview on smart charging and how the flexibility associated with charging an EV can be utilized as well as an overview of the involved market actors and their objective in the charging infrastructure system.

2.2.1. Types of Charging Stations

There is a wide variety of solutions to recharge EVs. Generally, charging stations can be categorized by the method of electricity transmission, which can either be achieved using a cable (conductive) or wireless using a pair of coils (inductive). While the former is standardized and widely available in vehicles today, the latter is limited to prototypes and individual technical solutions.

Conductive charging stations can further be divided into charging stations using alternating current (AC) or direct current (DC). The reason for this categorization is based on the battery within EVs that needs DC to be charged whereas the power grid operates with AC. As a consequence, the power needs to be converted from AC to DC which can either be done by the vehicle itself or the charging station. Due to weight and volume restrictions within an EV, the power of the on-board charger is lower compared to DC charging stations, which is why AC charging is also referred to as *slow charging*. AC charging stations cover a range of 3.6kW up to 43kW and are the most common and popular method of charging due to their lower cost of installation (Levinson and West, 2018). DC charging stations, on the other hand, are not limited in size and hence can provide higher power of 50kW up to 350kW. This is why they are also referred to as *fast charging*. Due to the additional infrastructure needed to transform AC from the grid to DC, DC fast chargers are significantly more expensive compared to AC charging stations (Levinson and West, 2018).

Besides their disparity in electric current, charging infrastructure can also be differentiated by their plugs. In recent years, different standards for various regions have been developed. A selection of these standards is presented in the following. While in America, the *Type 1* plug (SAE J1772) is defined as the standard plug for AC charging (Hardman et al., 2018), the standard plug for EVs in Europe is called *Type 2 Plug* or *Mennekes Plug*. They both have in common that they include pins for communication as well as AC power transfer. Both *Type 1* and *Type 2* plugs can be expanded by two additional pins to support DC fast charging, also referred to as the *Combined Charging System* or CCS. In addition, there is the CHAdeMO standard. This standard was developed by the CHAdeMO association formed by several companies, such as Nissan and Mitsubishi and is mostly used in Japan. The CHAdeMO plug is a DC only solution. An overview of the available connectors is shown in Figure 2.2.

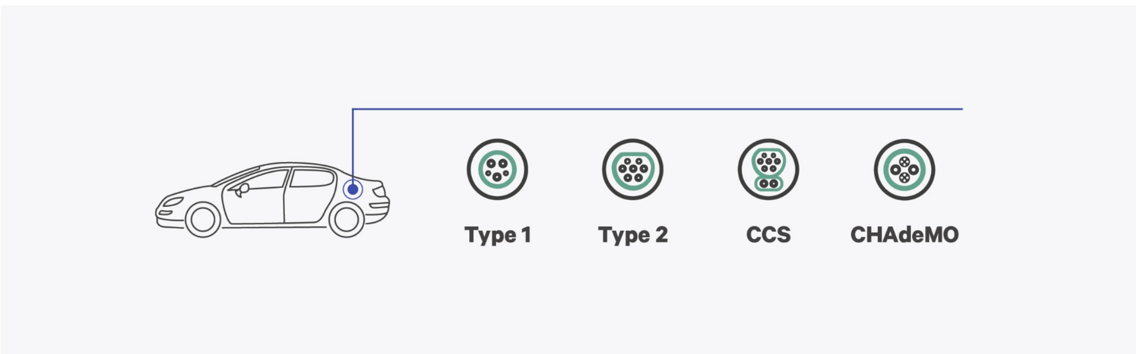

Figure 2.2.: Differentiation of Plug Connectors for Charging EVs (Wallbox, 2021)

The solutions developed in this dissertation can be applied to charging stations using any of the plugs mentioned above. Nevertheless, a differentiation between AC and DC charging infrastructure is provided to incorporate the variation in charging power and the associated time needed for charging. Besides their technical properties, the location of charging stations also impacts how charging infrastructure can be used.

2.2.2. Positioning of Charging Stations

With the goal of integrating charging sessions into the mobility pattern of EV owners in mind, the technical options presented in the previous section define the framework for EV owners and charging station operators. In this section, the focus is shifted towards locations where EVs can be recharged and models that help to find adequate sites for charging infrastructure.

Creating a broad charging network is essential to address the limitations of EVs, especially the reduced range. In recent years, several companies have focused on establishing a broad network of charging stations, that are available to the public. These public charging stations allow EV user to drive longer distances and also enable users without a private charging station to switch to an EV. In addition, they are perceived as a safety net and fallback option which EV owner require in order to take full advantage of their vehicles driving range (Wirges, 2016). A broad public charging network can also have a positive impact on EV adoption as many drivers are reluctant to purchase an EV without conveniently placed charging stations (Sweda and Klabjan, 2011).

However, for charging station operators, there is a need for a broad EV adoption before investing in charging infrastructure. Without a certain amount of EVs on the road, estimating charging demand is difficult (Pan et al., 2017; Cai et al., 2014), which leads to uncertainty of future revenue. This creates a dilemma where drivers delay their EV purchase due to limited charging infrastructure and investors hesitate to build charging stations without knowledge of EV demand (Sweda and Klabjan, 2011). This is also referred to as an "chicken and egg" problem that needs to be solved in order to foster EV adoption.

Research has tried to addressed this issue by providing sophisticated models that allow a demand driven positioning of charging infrastructure. To identify criteria that impact the utilization of charging stations, (Funke et al., 2015) define three categories: basic, macro and micro criteria. Criteria of the basic level describe factors that have the same impact at every location but may change in the long run and cannot be directly influenced by charging station operators. An example for a basic criterion is the total number of EVs registered as more EVs create a higher utilization of charging stations. Factors that are exogenous and specific for a single location are considered macro criteria. An example of a macro criterion is the traffic volume of a close by highway or a point of interest (POI). Charge point operators cannot directly influence these criteria but have the possibility to capitalize their advantages by positioning their infrastructure nearby. Micro criteria describe the characteristics of the charging site that are within direct dependency of the charge point operators planning. These include, for example, the number and power of charging stations, which should ideally be based on user preference.

The research of (He et al., 2018) and (Nicholas and Hall, 2018) provides an overview of different modelling approaches, use cases and assumptions needed for positioning and sizing of AC and DC charging stations. These models have in common that they rely on basic as well as macro criteria to determine the utilization of charging stations but ignore micro criteria. This is due to the fact that these two categories of criteria are more accessible and easier to quantify. To include micro criteria, agent based simulation can be used to analyze the decision of individual users for and against individual charging sites. The authors of (Pagani et al., 2019) describe a model that includes individual customer needs and their preferences to charge at different locations, such as at home, at work or at public charging stations. Nevertheless, there is still a demand for further research addressing the micro factors of locations and the individual user behavior of agents. This thesis contributes to this research gap and provides agent based simulations to further determine the utilization of charging infrastructure.

2.2.3. Smart Charging

One important factor for positioning and sizing a new charging station is the available grid connection, as it defines the upper bound of the total power charging stations can provide. Charging EVs induces a great load on the underlying grid and can lead to congestion on a power line. To avoid such a scenario, scheduling approaches for charging sessions have been developed, also referred to as *smart charging*. In a scenario without smart charging, EVs charge as fast as possible with a First-Come-First-Served (FCFS) approach. Thus, each EV is provided with the maximum charging power in order to increase the SoC of the battery and hence, to reduce the possibility of insufficient range. However, from a user's perspective, this range might not be immediately needed, which creates flexibility associated with the charging session. Flexibility is defined as the ability of a charging session to follow a different path of action at a given point in time to provide a service for another entity (Lehmann et al., 2019). The authors of (Ludwig et al., 2017) further differentiate between time and energy flexibility, where the former describes ones ability to change the energy consumption profile and the latter ones ability to shift the energy consumption profile.

Smart Charging is based upon this flexibility and is defined as an information system that optimizes the charging process towards one or multiple objectives in addition to the initial goal of reaching a desired SoC within a given time frame (Huber et al., 2019). There is a wide selection of objectives discussed in literature, such as peak shaving and valley-filling of a load curve (Colmenar-Santos et al., 2017) and providing re-dispatch (Staudt et al., 2018) or reserve power (Weiller and Neely, 2014).

As a consequence, there are multiple advantages associated with smart charging, especially for the grid operators. While uncontrolled EV charging can create bottlenecks in the power grid, controlled off-peak EV charging can eliminate the need for installing new capacity (Razeghi and Samuelsen, 2016). EVs can also be used to provide other services to the grid, such as ancillary services, in order to create additional profit to the EV owner (Hu et al., 2013) or ultra-short-term demand response (e.g. frequency control) (IEA, 2019). In addition, smart charging allows for the integration of much higher levels of energy provided by wind farms without excess electric production (Lund and Kempton, 2008). As a consequence, environmental smart charging approaches can reduce grid emissions (Razeghi and Samuelsen, 2016) as the usage of variable renewable generation can be more than doubled in some scenarios (Schuller et al., 2015).

Even though there are multiple possible objectives and areas of application for smart charging, the design of a smart charging system should focus on fulfilling mobility needs with high convenience and security (Huber et al., 2019). This finding is in line with the goal of this thesis. Especially with the mainstream market adopting EVs, there is a need to engineer smart charging approaches that respect the mobility pattern of EV owners. However, research shows that there is a great potential in the flexibility provided by EV charging sessions, which can provide additional benefits towards GHG emission reduction besides replacing ICEV. Thus, ecological advantages should not be neglected when optimizing charging sessions for the mobility pattern of EV owners.

Despite the benefits to the grid and environment, there are also challenges that need to be addressed. At the point in time where a smart charging approach needs to decide on a schedule for individual EV charging sessions, there is an uncertainty with regards to the future state of multiple dependencies of the smart charging system. For example, from a grid perspective, there is uncertainty towards the renewable energy generation, prices at the spot market and state of the grid. But user behavior also cannot be predicted with absolute certainty. This uncertainty poses a challenge for EV charging, as unexpected user behavior prevents an accurate and easy prediction of the charging flexibility (Noel et al., 2019b). Furthermore, smart charging schedules cannot only be beneficial for the grid but can also induce high loads in the system. Especially if a large group of EVs reacts to exogenous price signals, the additional load can aggregate to peak consumption (Flath et al., 2014).

Smart charging approaches need to cope with this uncertainty in order to fulfil their objectives. Based on the use case and the requirements set by the system, there are multiple methods described in literature that can provide charging schedules while optimizing one or more objectives. As an example, heuristics can be used if a short run time is required and data availability is low. Flath et al. (2012) show that heuristics can greatly reduce the individual electric energy cost with very low information requirements. In their research, they identify the "as-fast-as-possible" heuristic as a benchmark to analyze the feasibility of any given driving profile whilst considering EV battery restrictions. For more sophisticated smart charging approaches, linear programming is suitable for scheduling both EV fleets as well as individual EVs (Hu et al., 2013).

Every smart charging approach has in common, that data is needed to evaluate its performance and in order to make informed decisions for future charging schedules. While more information typically leads to better charging schedules, in a real world implementation, perfect foresight of all necessary parameters is connected to either a huge effort or is impossible (Flath et al., 2012). As a consequence, operators of charging infrastructure need to prioritize their effort on relevant data for smart charging to optimize their objectives. In their work, Schuller et al. (2015) show that trip information, for example, is more relevant than charger availability to utilize EV flexibility. The authors of (Hu et al., 2013) show that a linear approximation of the SoC of an EV is acceptable for smart charging approaches. Within this thesis, uncertainty in user behavior is addressed in more detail in Chapter 5.

Besides re-scheduling charging sessions, there are also several technical extension of smart charging. While the primary use case is to charge an EV, they can also provide electricity back to the grid. This concept is referred to as bidirectional charging and offers even more flexibility to smart charging approaches. Depending on where the energy is requested, bidirectional charging can further be categorized into "Vehicle-to-Home" (V2H) or "Vehicle-to-Grid" (V2G).

In a V2H scenario, the EV is connected to the energy management system of a house. The system then has the possibility to charge and discharge the vehicle to optimize the local energy consumption. As an example, the EV can be used to provide backup power (Shin and Baldick, 2017) or to act as an offline uninterruptible power supply (Monteiro et al., 2017). In combination with Time-of-Use tariffs, Colmenar-Santos et al. (2017) show that V2H can save up to 50% of energy cost. V2H can also have a positive impact on the decarbonization of energy generation if it is combined with a photovoltaic (PV) power plant (Noel et al., 2019b). In this scenario, excess energy generated throughout the day is stored in an EV and delivered back to the home over night. Usually, within V2H scenarios, the objective is to provide a benefit to the EV and home owner.

V2G, in comparison, uses bidirectional charging to provide energy back to the grid. Here, the most frequent research topics focus on renewable energy storage and integration, grid stability, batteries and distributed services (Sovacool et al., 2017). Set side by side to stationary energy storage, EVs with V2G can provide battery capacity at no or little additional cost (Noel et al., 2019b) and hence have a great potential to support the grid in the short- and long-term. On the other hand, EVs are not stationary and their dynamic nature has to be taken into account.

This section highlights that smart charging can provide benefits to different stakeholders in the energy sector, infrastructure providers as well as to owners of EVs. In order to gain a better understanding of the objectives and characteristics of the market participants involved in EV charging, the next section will provide additional information on the EV charging ecosystem.

2.2.4. Market Actors

For a successful and comfortable charging experience, a reliable cooperation of different market actors is needed. Even though the owner of an EV does not interact with every single market actor, it is still relevant to get an insight into their responsibilities and objectives. For simplicity, this section focuses on market actors with a direct impact on charging sessions. A detailed description of all relevant actors is provided in (Linnemann and Nagel, 2020).

Generation Every charging session starts with power generation. While EVs do not have "tailpipe" emissions as ICEVs, the GHG emissions associated with electromobility occur at the level of the electric energy generation. Power generators, in general, can be classified into renewable power sources and depletable power resources, where the latter are the primary cause for emissions. The energy mix provided by power generators defines the actual emissions of EVs and consequently GHG savings are higher when the carbon intensity of power generation is low (IEA, 2019). In addition, carbon emissions vary with time as the share of renewable energy sources depends on external factors, such as wind and solar energy availability (Huber et al., 2020). Besides GHG emissions, generators also have an impact on the energy price. The cheaper energy is generated, the cheaper EVs can be charged.

Transmission and Distribution Grid To ensure that electricity is available at a charging location, both a transmission as well as distribution grid is needed. The former is responsible to transport electricity over long distances, for example from an offshore wind park to a charging station in the south of Germany. The latter is in charge of last-mile-delivery from selected nodes in the grid to the end consumer. The main objective of grid operators is to ensure a stable operation. For EV charging, this causes a focus of this group of actors on power flow rather than the actual delivered energy.

Charge Point Operator The Charge Point Operator (CPO) is responsible for the installation of the charging station and its operation, including service and maintenance. The CPO is not necessarily the owner of the location and can partner with multiple site owners to expand the charging station network. This will be addressed in further detail in Chapters 4, 6 and 7, where public charging stations are analyzed. The revenue of a CPO is typically generated through the difference in wholesale price and sales price of electricity. Consequently, the CPO's main objective is to provide as much energy to EV owners as possible. This can be achieved through either a direct sale to customers or through an Electro-Mobility Provider (EMP).

Roaming Platform A roaming or clearing platform is the intermediary between CPOs and EMPs. Through the roaming platform, CPOs have the possibility to allow as many EMPs as possible to gain access to their infrastructure using a standardized communication.

Electro-Mobility Provider The Electro-Mobility Provider (EMP) is the intermediary between multiple CPOs and the user of an EV. EV owners sign a contract with an EMP, which defines the conditions for them to access and pay for charging sessions. There are multiple tariffs available, like cost per minute, kWh or a charging flat rate. Consequently, for EV owners the EMP is the most important counterpart for EV charging. EMPs are profit-oriented and try to maximize their revenue based on the offered tariffs.

The focus of this thesis is on CPOs and the users of EVs. There are two main reasons for this. First, a wide variety of research on the successful integration of power generation and grid operation is available. As an example, Schuller (2013) provides an overview on the economics of renewable energy integration for EV charging coordination. The authors of Staudt et al. (2018) show how EVs can support the grid for re-dispatch. Second, CPOs have a significant impact on the number of charging stations available and hence on the charging network EV users can rely on. It is of great importance to engineer charging coordination strategies that includes CPO interests in order to grow the network. An overview of all market participants and their interactions is illustrated in Figure 2.3. To complete this picture, the next chapter focuses on the market actor that is in the center of this thesis: the user.

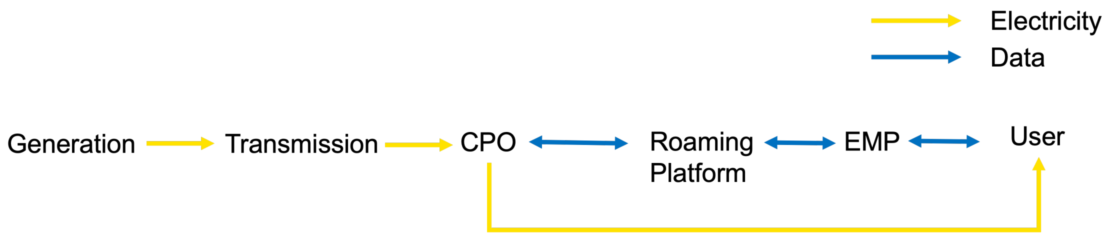

Figure 2.3.: Overview of market actors and energy as well as data flow

2.3. Users of Electric Vehicles

Vehicles, regardless of their drivetrain, fulfil not only instrumental but also symbolic and affective motives for their users (Steg, 2005). With respect to EV users, there is a need to understand their mobility pattern, to what extent EVs can fulfil their current needs, their motives to choose an EV and the challenges associated with the switch. These needs are not set in stone and can change with time. To better address user requirements during EV adoption, the TALC is used in this section, which is complemented with an analysis of psychological factors that foster and hinder EV adoption.

2.3.1. Electric Vehicle Users in the Technology Adoption Life Cycle

The *Technology Adoption Life Cycle Model* describes the market penetration of any new technology with regards to the progression in the types of customers in the course of its life cycle (Moore and McKenna, 1991). Within the model, customers are classified by their sensitivity to risk, where each group has a different set of needs and reactions to new innovations (Meade et al., 2006). There are five distinctive customer groups described in the TALC, which are the innovators, early adopters, early majority, late majority and laggards (Mogull, 2021). While the first two groups are referred to as the early market, the latter are called the mainstream market.

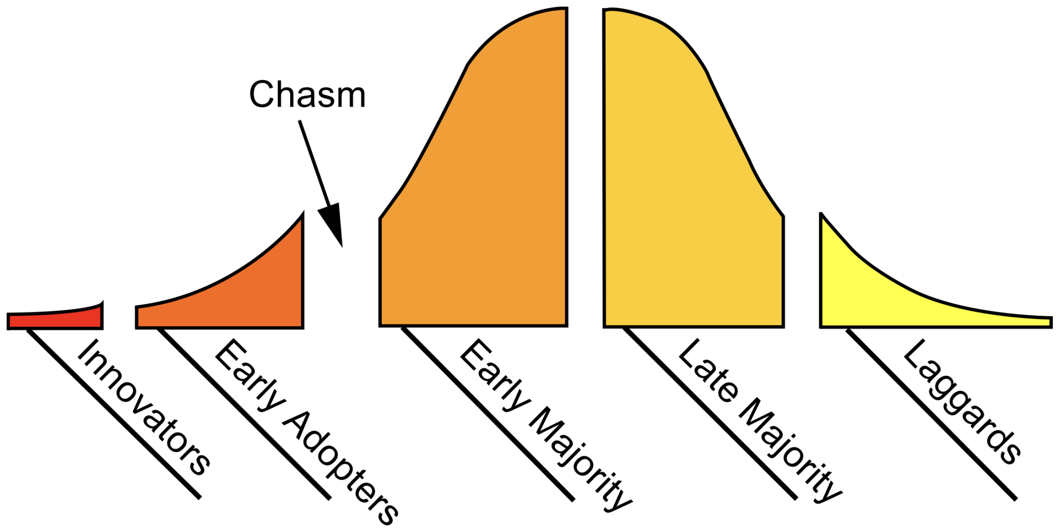

Figure 2.4.: Technology Adoption Life Cylcle (Meade et al., 2006)

Early Market Innovators are defined as the first 2.5% of market share, who adopt a new technology and are characterized as being able to cope with a high amount of uncertainty (Mogull, 2021). A typical innovator is a technology enthusiast, who adopts a new technology primarily because it is new and who is prone to developing her or his own solutions to using the product successfully (Mogull, 2021). For EV adoption, this translates to a customer group capable of changing their mobility behavior to account for longer charging time, reduced range and locating charging stations.

With increasing adoption of EVs, the customer base is broadened to also include the early adopters. This customer group represents an additional 13.5% of market share and includes consumers that are motivated by a high-risk-high-reward mentality but, in comparison to the innovators, require a more measurable application of the technology (Mogull, 2021). Early adopters have a good understanding of technology and are able to appreciate the benefits of EVs, without relying on a well-established reference for their buying decision (Feng et al., 2020). In the USA, as an example, it took 6 years to transition from innovators into the early adopter stage, which was finally accomplished in 2015 (Yong-Tae and Sung-Wook, 2019).

Overall, the early market consists of users that are able and willing to adapt their behavior in order to foster EV adoption. Within recent years, they bought EVs and thereby helped to develop the market and improve the existing technology.

Mainstream Market Compared to the early market, mainstream market consumers are characterized as cautious and resistant to both adopting new technologies as well as changing processes and behavior (Mogull, 2021). The composition of the mainstream market is dominated by the early majority, who are also referred to as the pragmatists (Moore and McKenna, 1991). Unlike the early market, they need to establish greater trust in the innovation (Mogull, 2021) and therefore, due to their pragmatic nature, might wait until there is a need to upgrade. While the early majority is accepted as leaders by the late majority, they are rejected by the laggards.

Chasm The adoption of a new technology by the mainstream market is crucial for the commercial success, due to its large market share of 84% (Mogull, 2021). Nevertheless, as a result of the differences between the customers of the early and the mainstream market, innovations frequently fall into a *chasm* marked by a decrease in sales (Meade and Rabelo, 2004). The early majority might delay a purchase in anticipation of a future update that meets their requirements, creating a dilemma where the wait for an update delays the widespread adoption of an innovations and hence also the possible investments into future updates (Mogull, 2021).

Innovations need to address this chasm in order to succeed. In their work, Moore and McKenna (1991) focus on possible actions to cross the chasm, such as the "niche strategy" where rather than following a sale-driven market, companies shift towards a market-driven strategy and design the innovation in a way that it addresses the needs of a specific customer group, thus addressing the pragmatism of the early majority. Gourville (2005) builds upon this work and further differentiates innovation into four quadrants by the degree of behavioral change required and the degree of product innovation. Based on these two dimensions, he differentiates innovations into the death, long haul, tinkering and home run cell. This classification is shown in Figure 2.5.

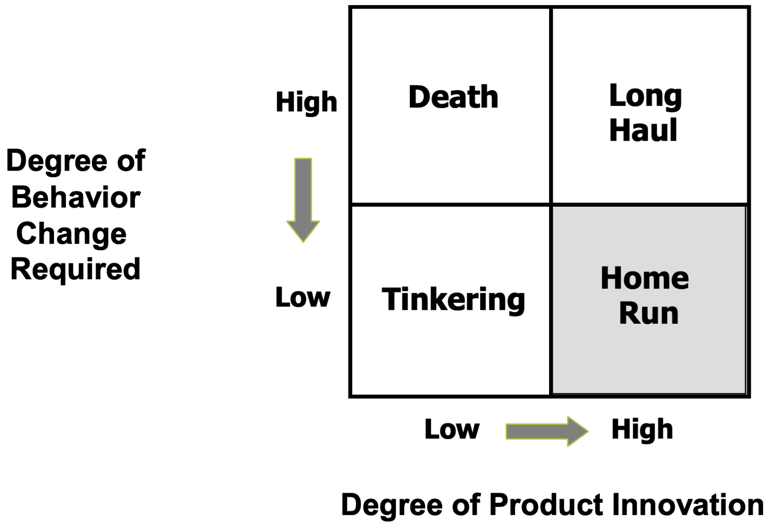

Figure 2.5.: Mapping Product Change and Behavior Change (Gourville, 2005)

While the home run includes innovations that provide great technological and limited behavioral change and thus suggest a high acceptance from the customer, the other cells have a lower likelihood of adoption. In the death cell, a tremendous change in behavior is required, while the technological improvements are small. Innovations in this cell, as indicated by its name, have a small chance of success. In the tinkering cell, little behavioral change is required, but the technological improvement is also limited. Most incremental product improvements fall into this cell. In the long haul, there are innovations with a great technological change and improvement that are linked to considerable behavioral change. EVs are located in this cell and hence, strategies are required to address the long haul.

In his work, Gourville (2005) suggests that companies can proactively address the behavioral change required for an innovation. With the strategy *make it behaviorally* *compatible*, companies can modify the innovation and the surrounding ecosystem to reduce the impact on user behavior. The question remains how such a system should be designed for EVs and how user behavior can be addressed in both the charging infrastructure provided to EV users as well as the charging strategy used. This knowledge gap is addressed within this thesis and possible solutions are provided. Besides the existing information based on the classification of the risk-taking behavior of customers, there is also information available on users that have already bought and used an EV. The factors that have driven these users to purchase an EV are discussed in the following.

2.3.2. Characteristics of Users Adopting Electric Vehicles

The number of EVs is constantly increasing with currently 10,907,150 EVs on the road worldwide (ZSW, 2021). This trend is not limited to cars. At the end of 2018, the global stock of electric two-wheelers increased to 260 million and the stock of electric busses to 460,000 IEA (2019). With this growing amount of EVs on the road, the number of EV users also rises. As a consequence, there is already a large group of existing EV users and it is important to get a detailed understanding of who decides to buy an EV, what their needs and challenges are and why others delay or avoid an EV purchase.

Not every user is the same and users can be classified using different characteristics, such as where they live, the number of people in the household, how much they earn and many other aspects. In their work, Sodenkamp et al. (2019) find that performance indicators vary drastically between different driver segments which emphasizes the necessity to conduct segment-specific assessments. In the past years, there was only a small number of EV users with characterizations different to the average vehicle owner. In 2015, as an example, a typical EV user was male, with a high educational degree and a relatively high income who lived in a rural area in a house with a designated parking spot (Frenzel et al., 2015). This is in line with the TALC where the innovators and early adopters can cope with a higher risk, such as the financial investment into an EV, due to their higher income. These users from the early market are capable to utilize more range of the vehicle, as drivers who display a higher degree of risk seeking tend to charge their EVs at a lower SoC (Hu et al., 2019). Even though their market share is small, early adopters are a relevant customer group for the success of an innovation, as they are "the individual to check with" before using a new technology (Rogers, 1983) and thus act as a reference to users of the mainstream market.

While it is important to learn from these early adopters to make the EV ecosystem *behaviorally compatible*, this biased user group cannot be used exclusively for the development of charging strategies. In literature, focus on early adopters is a common sample bias, even though their input is important as they are the only ones with direct experience of EVs (Rezvani et al., 2015). Users in the mainstream market on the other hand, are sceptical of the latest technical claims and are resistant to modify their behavioral pattern (Gourville, 2005). In order to develop charging strategies for this user group, data of current mobility behavior using ICEV should be analyzed (Sodenkamp et al., 2019; Luo et al., 2018). Within this thesis, the focus is on mobility data that is not exclusive to EV owners, but rather a wide collection of trips done with both EVs as well as ICEVs. This ensures that the impact of the sample bias introduced by early market users is reduced and the current user behavior of the mainstream market is adequately considered.

There is a variety of other influences that have an impact on a user's willingness to purchase an EV, such as the sector they operate in. The authors of Kaplan et al. (2016) show that the sectors agriculture, forestry and fishing, public administration and defence have a low positive attitude towards EVs whereas companies in the high-technology sector have higher positive attitudes. For commercial fleets, factors that foster initiatives for EV adoption are for example organizational innovativeness (Globisch et al., 2018). The size of a company, on the other hand, has no notable impact on EV adoption (Sierzchula et al., 2014).

Besides socio-demographic influences, other factors, such as political initiatives, foster EV adoption. In order to comply with the Kyoto Protocol, governments all around the world see a need to reduce GHG (Longo et al., 2016). As a consequence, they subsidize EV purchases for a faster market diffusion (Plötz et al., 2014b), for example, with exemptions from purchase tax and VAT (Bjerkan et al., 2016) or tax reduction on company cars (Koetse and Hoen, 2014). On an individual user basis, there are indications that psychological factors, such as the interest in driving an environmentally-friendly car foster EV adoption Plötz et al. (2014b).

2.3.3. Challenges for Electric Vehicle Users

Even though there are multiple advantages linked to replacing an ICEV with an EV, there are still users that do not plan or delay an EV purchase due to a wide variety of reasons. In this section, limitations of EVs and their perception by users are discussed in more detail.

Cost EVs typically have a higher purchase price due to the battery installed in the vehicle but lower operational cost compared to an ICEV. Especially the purchase price has a negative and highly significant influence on EV adoption (Liao et al., 2017). This has been demonstrated in the literature, where purchase price is stated as the most frequent as a factor for EV market diffusion models (Gnann et al., 2018). When users are asked about their willingness to pay for an EV, research shows that they are unwilling to pay large premiums, even when additional information about future savings on fuel is provided. This changes once a user gains experience with an EV. In this case, up to 25% of users are willing to pay a premium of up to 10,000$ (Larson et al., 2014). This focus on cost can also be noticed in commercial fleets, where the total cost of ownership is a major factor (Herrmann et al., 2018). Based purely on costs, many fleet managers are discouraged from the integration of EVs into their fleet until prices of the vehicles are considerably decreased (Sierzchula, 2014). Overall, life cycle cost analysis shows that EVs are not yet competitive due to the price of the battery, but advancements in technology will likely make them competitive in the future (Ayodele and Mustapa, 2020).

Range Another limitation frequently brought up by both private as well as commercial EV owners is the reduced range of the vehicles (Franke et al., 2012). Even though the technological progress constantly increases the range of EVs, the psychological fear on limited driving range still keeps consumers from adopting EVs (Guo et al., 2018). Although, in 2014, EVs where already able to cover up to 80% of urban trips and between 8% to 28% of users could have replaced their ICEV without any change in driving pattern (de Gennaro et al., 2014), the fear of mobility constraints and doubts about the reliability of EVs counteracted their procurement (Globisch et al., 2018). This fear is also referred to as *range anxiety* and describes a scenario where an EV user is scared to fully deplete the vehicles battery in the middle of a trip, leaving the driver stranded (Neubauer and Wood, 2014). As a result, EV users might only take trips of 145 km (90 miles) even though the battery is capable of driving 160 km (100 miles). For modern EVs, research suggests range anxiety is primarily a psychological rather than a technical barrier (Franke et al., 2012). In addition, the extent at which users experience range anxiety changes over time. While in the initial phase of EV use, drivers cannot estimate the remaining range of their vehicle and hence experience range anxiety, this changes for experienced EV drivers (Rauh et al., 2015). There are multiple ways to address the fear of range anxiety, increasing range being the most apparent. Due to advancements in battery and cell design, the range of EVs is constantly increasing as is illustrated in Figure 2.6.

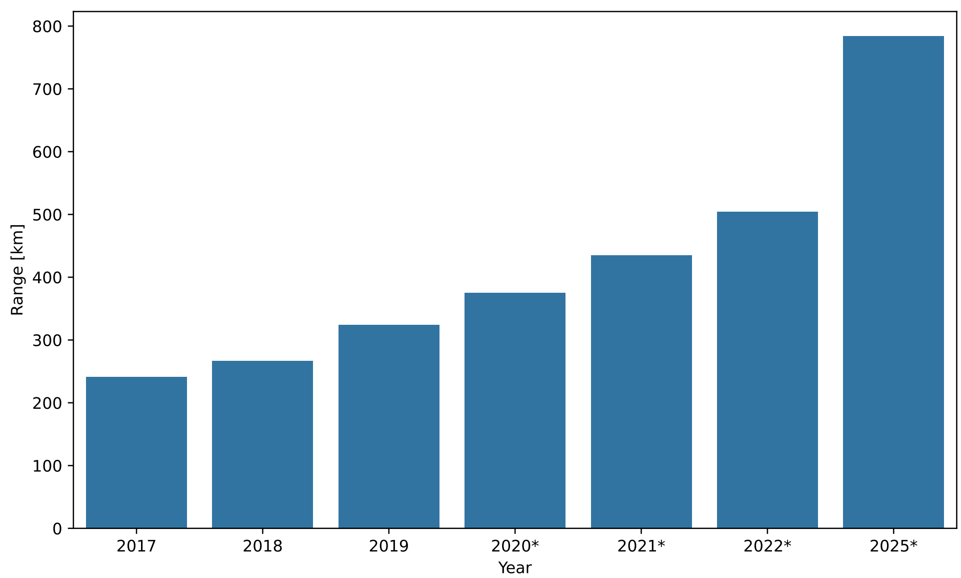

Figure 2.6.: Average Range of EVs in Germany (* Prognosis) (Horváth & Partners, 2020)

With a higher SoC, the range of EVs increases and the fear of depleting the battery decreases. One way to achieve this, is to provide charging infrastructure wherever the vehicle is parked. Consequently, access to additional charging infrastructure reduces range anxiety (Neubauer and Wood, 2014).

Charging Infrastructure The number of public charging stations is constantly increasing. In 2019, 598,217 slow and 263,802 fast charging stations were in operation worldwide, which is a notable increase compared to a total of 537,682 charging stations in 2018 (IEA, 2020). When charging an EV, users have to address two main decisions. First, they have to decide on the location they want to charge at. Due to the wide availability of electricity, there are multiple potential options, such as charging at home, at the supermarket, at work or at the highway. Second, they have to consider the time they can or want to spend charging. While refueling an ICEV typically requires an additional trip for the user, charging can be integrated into the current mobility pattern. As a consequence, the planned dwell time describes a main restriction of the total charging time. This concept of charging at the end of a trip is called *destination charging*. Destination charging brings significant convenience to EV owners as they are able to take care of other tasks instead of waiting for the vehicle (Luo et al., 2018). One destination frequently visited by EV users is their home. Thus, home charging is the most important charging station for many EV users (Funke et al., 2019) but is not available to everybody. Especially within cities, EV users might not have a dedicated parking spot and hence need to rely on public charging stations. For these users, public destination charging has to fit into their mobility pattern and is discussed in more detail in Chapter 4. Overall, research has shown that the availability of charging infrastructure is strongly linked to EV adoption (Sierzchula, 2014) and hence should be focused on even further.

In this chapter, an introduction to the foundations of individual electric mobility is presented. These foundations define both the possibilities when adopting EVs, but also present possible barriers and limitations that have to be considered when designing charging strategies. Based on these characteristics of EVs, charging infrastructure and users, the following chapters analyze how to develop charging strategies within each quadrant of the matrix presented in Figure 1.1.

Part II.

Charging Private Electric Vehicles

Introduction to Part II

Vehicles owned by private users account for 38% of the overall vehicle fleet (KBA, 2021) and are used, for example, for short distance commuting but also for going on vacation and traveling abroad. While the former can be accomplished using private charging stations at home, the latter two require a broad public charging infrastructure. Part II therefore focuses on the needs and possibilities of privately owned EVs and, based on empirical data of trips, analyses two uses cases that address the potential of private and public charging infrastructure, respectively. First, the opportunity for sharing private charging infrastructure in urban areas is evaluated. This includes an identification of user groups with similar mobility patterns and a novel matching approach to determine users with a complementary need for charging. Second, the scope for charging infrastructure is broadened to also include public charging stations. Based on generic as well as real utilization patterns from the city center of Karlsruhe, the importance of user behavior for public destination charging is demonstrated and quantified. This covers both a framework to determine the losses in demand as well as a real world case study. Overall, this part provides a broad analysis on the potential of private EV users and charging station operators to coordinate private charging behavior at private and public charging stations and to provide corresponding infrastructure to allow private users to maintain their current mobility patterns using electric vehicles.

Chapter 3.

Sharing of Private Charging Stations at Home

There is a variety of possibilities to charge an EV, such as charging at home using the private parking lot. Charging at home presents a comfortable opportunity, as no additional trips are required. In this chapter, the possibility to extend the use of private charging stations at home by sharing them based on the mobility pattern of users is addressed. This approach offers the comfort of charging at home to neighbors who might not have the technical requirements, while simultaneously reducing investment costs for charging infrastructure by increasing the usage rate. Using empirical data of trips conducted throughout Germany, clusters of vehicle owners with similar travel patterns are identified. These clusters are then used to determine possible groups of users that are most likely able to share a private charging station without a negative impact on their mobility needs. To achieve this goal, a novel algorithm is introduced that allows multiple travel patterns to be matched. The results show that there are user groups that can share a private charging station, especially when their mobility patterns complement each other. Furthermore, the results show that not every travel pattern provides the same benefit to a shared charging infrastructure. Nevertheless, the concept of shared charging stations in urbans area promises great benefit to the involved parties and should be further addressed in future research. This chapter comprises the results of the working paper (Schmidt et al., 2022) and is a joint work together with Philipp Staudt and Christof Weinhardt.

3.1. Introduction

Charging an EV can both be very time intensive and require prior planing by the driver if insufficient charging stations are located nearby. However, charging experience can also be comfortable and fully integrated within the mobility pattern of the user. While the former should be avoided in order to foster EV adoption, the latter allows for an effortless transition towards EVs. Within this chapter, the most important location to charge an EV for both early adopters as well as future users is analyzed, which is at home (Funke et al., 2019). Charging at home is preferred by most EV users (Zhang et al., 2018) as it allows them to charge their vehicle without the need for additional trips. In addition, it is convenient as there is no added driving distance due to seeking a location to recharge (Sweda and Klabjan, 2011) and no charging queues.

The home of a vehicle owner is a frequently visited location with an extended dwell time and therefore, providing charging infrastructure at the private parking lot allows EV users to fully charge their vehicle, which is the ultimate goal of each charging session (Luo et al., 2018). Further, the authors of Sodenkamp et al. (2019) show that exclusively using private charging infrastructure at the primary location of users allows for the electrification of 67% of the distance traveled. This highlights that the home of EV users is a promising location for charging infrastructure from both a technical, but also a comfort perspective. Consequently, especially among early adopters, there is a large share of EV users with a single-family house and a dedicated parking lot with a possibility to charge (Frenzel et al., 2015).

However, not every vehicle owner has access to such private charging infrastructure. In Germany, around 40% of vehicle owners do not have a dedicated parking lot (Plötz et al., 2014a) and therefore, have to rely on public charging infrastructure. But the accessibility of parking spaces differs between life styles and housing opportunities. Around 75% of vehicles owned by users living in a private home have a parking lot on the users property (dena Prognos, 2020). Further, the possession of a private parking lot does not guarantee the access to a charging station, as some locations do not have a sufficient grid capacity for a charging station or the parking lots are located in a semi-public location, such as an underground car park.

Besides differences due to living conditions, the location of the home also has an impact on the ability to provide charging infrastructure at a private parking lot. While vehicle owners in rural areas mostly have access to private parking lots, the share decreases to around 50% within cities (dena Prognos, 2020). In order to foster EV adoption, there is a need to provide sufficient comfortable charging infrastructure within cities even if the vehicle owners do not have the ability to install a private charging station, whether it is due to the absence of a private parking lot or due to technical limitations of the grid. In this context, sharing a private charging station has the potential to provide a wide availability of charging infrastructure to a community and is further analyzed in the following.

Sharing a private charging station (i.e. a wallbox) can provide benefits to all parties involved. For the owner of the wallbox, the newly installed charging station provides a comfortable solution to charge the EV at home. As the installation requires a fixed investment, sharing the infrastructure can help to improve the capital efficiency. In addition, there is a lot of flexibility when charging an EV. The research of Schäuble et al. (2017) shows that a typical EV is charged every third or fourth day, leaving the wallbox unused most of the time. This flexibility is not limited to time flexibility, but also applies to energy flexibility. As an average EV travels around 38km per day (Franke and Krems, 2013), the typical range of an EV is sufficient to delay charging sessions even further. From a neighbor's perspective, using a shared charging station can provide a similar experience as a private wallbox without the need to invest. Furthermore, it also enables neighbors without the possibility of installing a wallbox to profit from the comfort of home charging. Consequently, there is a potential for both the owner of a wallbox as well as the neighbors to benefit from a shared charging station. The challenge that arises from this setup is the possibility of users blocking the access to the wallbox and therefore creating a negative impact on the mobility of others. To gain insights on the technical possibility to share a wallbox and to answer Research Question 1, a novel approach to match users is introduced in this chapter. This algorithm allows to identify groups of vehicle users that have the potential to share a private charging station without a negative impact on their mobility needs.

3.2. Methodology

In this section, the empirical data of mobility patterns in Germany is presented, which is used in this chapter. Based on the data of individual trips of households, a cluster analysis is conducted to identify users with similar mobility patterns. Using cluster analysis helps to generalize the findings of this work and builds a foundation for predicting the behavior of users outside the analyzed data set. The clusters are then used to match mobility patterns into groups that have the potential for wallbox sharing. The exact approaches are presented in the following.

3.2.1. Data

As discussed in Section 2.3, solely using data of current EV users introduces a sample bias and should therefore be avoided when focusing on the mainstream market. Furthermore, the authors of Luo et al. (2018) find evidence that ICEVs and EVs are driven and parked in a similar way. As a consequence, this analysis is based on a representative data set of recorded trips within Germany, known as the *Deutsche Mobilitätspanel* or *MOP* (Engl.: German Mobility Panel), that is independent of the drive train of a vehicle (Eisenmann et al.). The MOP is continuously being updated since 1994 and on average includes the mobility pattern of around 3,100 people living in 1,850 households (BMVI, 2021). For the analysis, data from January 2nd 2017 to the 2nd of January 2018 is used. To address the objective of this study, the data set is limited to households living in urban areas. In total, the resulting data set includes 534 households with 874 participants. An overview of the total distance traveled by the users within the data set is provided in Figure 3.1.

3.2.2. Clustering of User Behavior

The main objective of clustering is to identify users with similar mobility patterns. There are multiple approaches to cluster data, such as density based and centroid based algorithms. Within the use case described in this chapter both are tested and the latter is selected as it shows better results. The centroid based algorithm is further introduced in the following.

One of the most common clustering algorithms is k-means due to its simple and fast

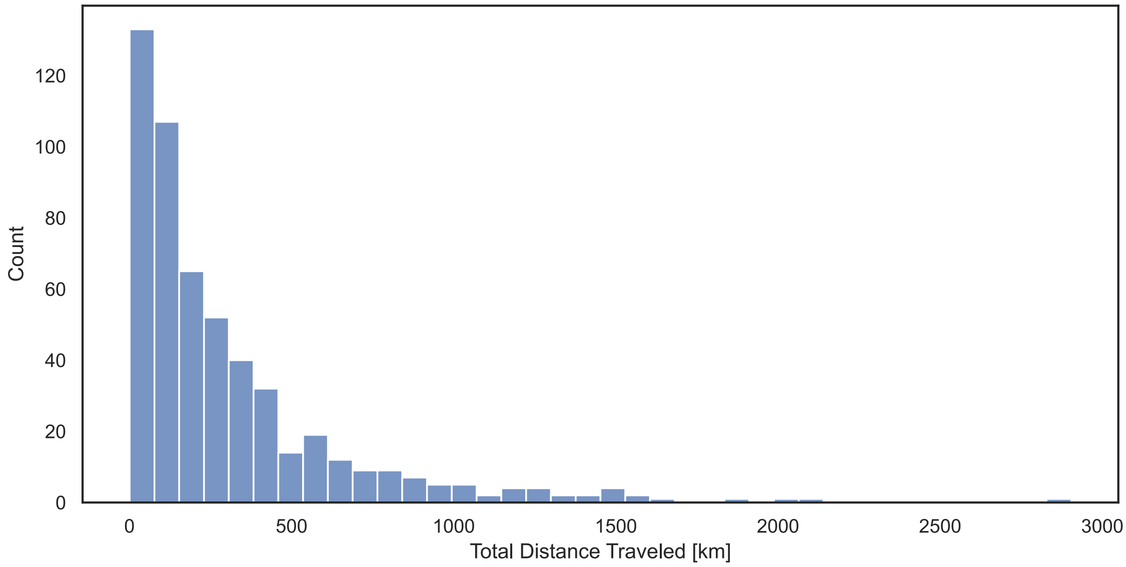

Figure 3.1.: Distribution of Total Distance Traveled by Users

clustering technique (Kodinariya and Makwana, 2013; Yuan and Yang, 2019). The objective of the k-means algorithm is to divide a data set of M points in N dimensions into K cluster in a way, that the within cluster sum of squares is minimized (Hartigan and Wong, 1979). This is done using an iterative approach. In a first step, K arbitrary data points are selected as the initial centroids. Then, the remaining data points are assigned to the closest centroid based on the euclidean distance. In the next step, for each cluster, the new centroid is determined as the mean of all members. A full description of the algorithm is provided by Gupta and Chandra (2021).

Dimensions Using the data of the MOP allows for a defined characterization of mobility patterns. An overview of all dimensions is provided in Table 3.1. Mobility patterns of households differ on weekends compared to weekdays. To incorporate this characteristic, the dimensions used for clustering are split into individual variables for weekdays and the weekend. Further, using the Pearson-Bravais-Correlation, the number of dimensions is reduced. With a correlation of 0.904 and 0.900 between the *round trip count* and *trip count* of weekdays and weekends, the former is dropped. Further the *average end on weekends* is correlated with -0.855 with the *average start on weekends* and the *time elsewhere* on weekdays and on the weekend is correlated with the *time home*. Consequently, for clustering, only variables with an asterics in

Table 3.1.: Dimensions of mobility patterns using the MOP dataset.

workday variables	**weekend variables**
workday Timehome*	weekend Timehome*
workday Tripduration*	weekend Tripduration*
workday Mileage/trip*	weekend Mileage/trip*
workday Tripcount*	weekend Tripcount*
workday Roundtripcount	weekend Roundtripcount
workday avgStart*	weekend avgStart*
workday avgEnd*	weekend avgEnd
workday Tripcount*	weekend Tripcount*

Table 3.1 are considered.

Selection of K In the k-means algorithm, the total number of clusters K is an exogenous variable and has to be defined by the user in advance. Within this work, the Silhouette Coefficient Algorithm is used to determine the best total number of clusters K. The Silhouette Coefficient Algorithm combines two factors, which are cohesion and resolution, where the former defines the similarity of objects within a cluster and the latter defines the dissimilarities to other clusters (Yuan and Yang, 2019). The coefficient is defined on a range of -1 to 1, where negative values indicate a probably false allocation to a cluster and values close to 1 indicate that points are very distant from neighboring clusters (Lleti et al., 2004). A complete definition of the Silhouette Coefficient Algorithm can be found in the work of Yuan and Yang (2019). Using this algorithm, the ideal number of clusters is defined as 7 in this use case. The range of silhouette coefficients is presented in Figure 3.2.

Overall, Figure 3.2 shows that the Silhouette Coefficient is not very high for all the K investigated. Within the range of 2 to 10, $K = 7$ has the highest Silhouette Coefficient and is therefore used in the following to cluster users with similar mobility patterns.

3.2.3. Identified Clusters of User Behavior

Using the clustering approach introduced in the previous section, a total of 7 clusters is identified and is further described in the following. A complete overview of all

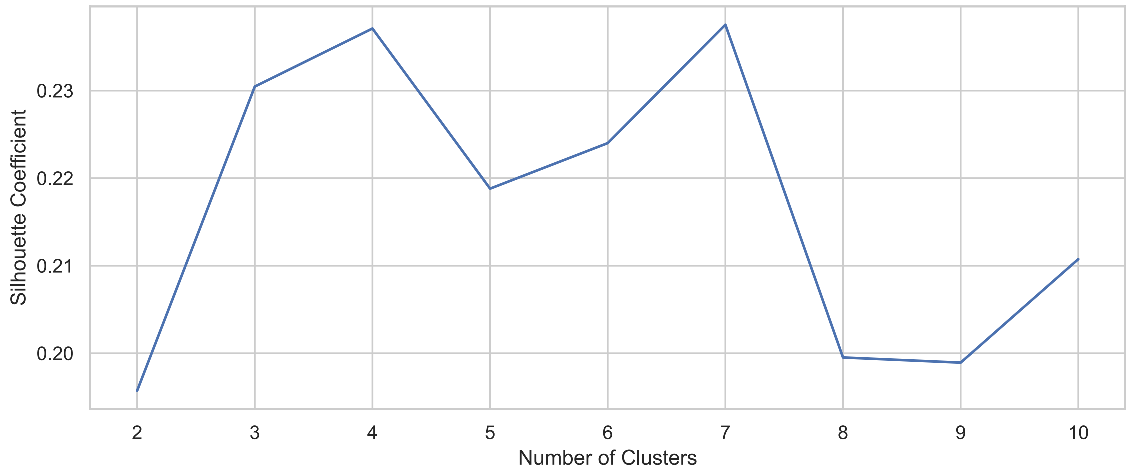

Figure 3.2.: Silhouette Coefficients for different numbers of clusters

variables is provided in Table 3.2. For improved readability, each cluster is given a name describing its key properties. Furthermore, an overview of employment status and year of birth of the members in each cluster is given in Figure A.1 and A.2 in the Appendix.

Cluster 1 - "High Frequent Commuter" With a share of 28%, Cluster 1 describes the second largest group among all mobility patterns. Members of this cluster have the highest trip count both on weekdays as well as on weekends and second highest trip duration with an average of 10.89h per day. Most of the trips during the week are commuting as well as running errands. Due to the large number of trips also on weekends, this cluster is referred to as the *High Frequent Commuters*.

Cluster 2 - "Local Workday Commuters" The third largest cluster is Cluster 2, with a share of 17%. Drivers within this cluster are characterized by a long time spent at home and shorter trip durations. Similar to Cluster 1, the purposes for trips during the week are mostly driving to work and running an errand. On weekends, members of Cluster 2 predominantly stay at home.

Cluster 3 - "Weekend Trips" Cluster 3 is characterized by a large heterogeneity in mobility patterns of weekdays and weekends. During the week, only a few small trips are made with the lowest trip count among all clusters. This changes on the weekend, where members spend more than 5 hours on average away from home.

Cluster 4 - "Frequent Local Errands" The fourth cluster is the largest cluster with a total share of 36% of all mobility patterns. Drivers within this cluster are mostly employed and retired singles or couples that have a similar mobility pattern as Cluster 1. Nevertheless, they can be distinguished from Cluster 1 by the short distances travelled for each trip. In addition, they have the second highest trip count on both weekdays and on weekends.

Cluster 5 - "Weekend High Mileage" In Cluster 5, there is a noticeable difference in distance traveled between weekdays and weekends. While the average distance of 34 km traveled on weekdays is already higher than most other clusters, the average distance is by far the highest on weekends with around 192 km. Members of this cluster use the vehicle for various purposes and are not limited to local destinations. One typical destination found in this cluster is a second home, which explains the long distances traveled on weekends.

Cluster 6 - "Frequent High Mileage" With a share of 0.75%, Cluster 6 is the smallest of all clusters. This is due to the unique traveling pattern of users in the cluster, who visit their home only for 1.25 times per week on average. Within each trip they cover long distances with an average of 400km on weekdays and 115km on the weekend and consequently, have the highest total distance covered of all clusters.

Cluster 7 - "Seldom at Home" 5% of all mobility patterns are assigned to Cluster 7, which is characterized by the short time spend at home. On weekends, most trips are related to errands and another 25% of trips lead to a second home, similar to Cluster 5.

3.2.4. Matching of Clusters

Using the clusters identified in the previous section, this sections defines a novel matching algorithm that allows for the identification of user groups most likely to share a wallbox without a negative impact on their mobility patterns. The basic idea behind this algorithm is to find complementary mobility patterns, which

Table 3.2.: Characteristics of the Identified Clusters

Cluster	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Distribution	28.09%	16.67%	7.30%	36.89%	5.24%	0.75%	5.06%
Workday Variables							
Tripduration [h/day]	10.89	3.35	0.16	4.00	5.45	12.47	3.25
Timehome [h/day]	13.66	20.31	21.98	19.33	17.231	15.31	10.37
Timeelsewhere [h/day]	8.15	3.01	1.98	3.86	5.67	6.19	12.97
Roundtripcount	1.47	0.61	0.02	0.91	0.57	0.25	0.29
Tripcount	4.37	1.39	0.09	2.16	1.79	0.70	1.34
Mileagetrip [km/trip]	23.79	16.17	1.71	11.76	34.32	399.71	25.25
Start [daytime]	10.02	12.31	3.00	12.09	11.03	12.88	10.63
End [daytime]	16.24	16.51	6.25	15.94	15.17	17.50	15.56
Weekend Variables							
Tripduration [h/day]	2.98	0.05	1.42	1.58	7.08	4.03	0.79
Timehome [h/day]	17.04	23.53	17.66	20.10	8.76	17.89	1.09
Timeelsewhere [h/day]	5.46	0.45	5.63	3.10	11.69	4.09	22.52
Roundtripcount	1.29	0.01	0.46	0.90	0.55	0.37	0.07
Tripcount	3.37	0.04	1.08	2.06	1.84	1.00	0.61
Mileagetrip [km/trip]	20.12	1.18	20.76	13.76	192.22	115.24	12.04
Start [daytime]	12.10	3.00	13.94	14.17	10.46	15.00	8.00
End [daytime]	15.23	7.00	15.81	15.48	17.94	11.50	16.75

is achieved through an even distribution of distances traveled each day by all members of a group. An example of a good fit can be a mobility pattern of a user working and commuting throughout the week, who is inactive on weekends with a user working from home with an interest in leisure activities on weekends. In this case, the wallbox can be used throughout the week by the first and on weekends by the second user. In order to achieve this, an iterative algorithm is introduced.

When matching two user's mobility patterns, they both have the potential to profit from a private charging station. However, the technical limitations of the private charging station as well as the ones of the vehicles have to be considered. To achieve this, two break criteria are defined at which the matching algorithm will not add any further users to the group. The first is defined by the power limitation of the charging station. Charging stations in private homes typically have a power of 11kW, as described in Chapter 2. Consequently, during one week, a wallbox can cover $d_{total}^{week} = 11kW \cdot 24h \cdot 7days = 1,848kWh$ or on an individual day $d_{total}^{day} = 264kWh$.

For the matching algorithm, this defines the upper bound when matching further users to a group. Assuming a medium size EV with an average consumption of 16 kWh/100km (Messagie et al., 2010), this translates to a maximum chargeable range per day of 1650km. Furthermore, the aggregated time of all vehicles spent at the location per day also defines an upper bound for the matching algorithm. Assuming a non-overlapping allocation of the vehicles to the charging station, the aggregated time multiplied by the charging power of 11kW defines the technical limitation of the vehicles. This converts into 68.75km/h of range. Consequently, no further users are added if their dwell time is insufficient to recharge their demand.

The objective of the matching algorithm is to create groups with an evenly distributed distance covered for each day, which is measured by the variance. Each cluster is represented by its center mobility pattern. Beginning with the initial first cluster, the algorithm iterates over all clusters and adds the representative mobility pattern of the cluster to the group that creates the lowest aggregated variance. In this algorithm, each cluster can be selected multiple times. The process is repeated until either the technical constraints of the charging station or the vehicles is violated. To ensure that each cluster is at least part of one matched group, each representative of a cluster is used once as a seed mobility pattern. As an output, the algorithm returns a sequence of cluster IDs that creates a potential group for sharing a private charging station.

3.2.5. Evaluation of Matching Algorithm

Using the matching algorithm, groups of users with a high potential to share a private charging station are identified. Nevertheless, the algorithm is based on clusters of mobility patterns and does not guarantee that such a group can operate successfully using a predefined charging strategy. In order to answer Research Question 1, an agent based simulation is implemented that resembles the behavior of individual users. Using the results of the simulation, the outputs of the matching algorithm are benchmarked against a random group of user as well as compared with each other.

Agent based Simulation In the simulation, the interaction of vehicles (agents) with a private charging station is modeled. At the initialization, a predefined set of agents is created. Each agent represents a mobility pattern from the MOP data set and is equipped with a 60kWh battery at an SoC of 50%. If one or more agents are at home at the beginning of the simulation, a random agent among them is selected for charging. The simulation then iterates through a week with $t \in [0, ..., 10080]$ minutes and follows the travel pattern of the agent. At departure, the simulation checks if the SoC is sufficient to cover the planned trip. If the range is lower than the trip, the simulation assumes that the agent will charge the required amount at a public charging station along the way. Upon arrival back home, a First-Come-First-Served (FCFS) charging strategy is applied. In case there is no active charging session at the wallbox, the agent will start charging. Otherwise, the agent will park without charging. FCFS was selected because it requires minimal interaction as charging sessions are only initiated at times where the user is at the vehicle. Consequently, the results represent a lower bound that can be further improved using more sophisticated strategies. As an output, the simulation provides the utilization of the wallbox throughout the week, as well as the charging behavior of agents and their covered demand.

Evaluation To answer Research Question 1, the identified clusters and the simulation are evaluated. The simulation provides insights on the extent that a group of EV users can share a private charging station. Furthermore, to evaluate the improvements provided by the matching algorithm both a random sample of users as well as a matched group are analyzed. The number of users sharing a wallbox has an impact on the chance of successful charging sessions. Consequently, the size of a group sharing a wallbox is increased gradually. For the random group, this is achieved through a random selection of a mobility patterns within the complete data set. The matched groups, on the other hand, follow the sequence defined by the matching algorithm. As an example, if the first cluster within the sequence is Cluster 1, a random user behavior within Cluster 1 is selected. The set of agents created this way are than used as the input for the simulation. To account for the impact of random selection, the simulation follows a Monte-Carlo approach. Each combination of group size and matched group is repeated 500 times in order to balance the results. An overview of the process is provided in Figure 3.3.

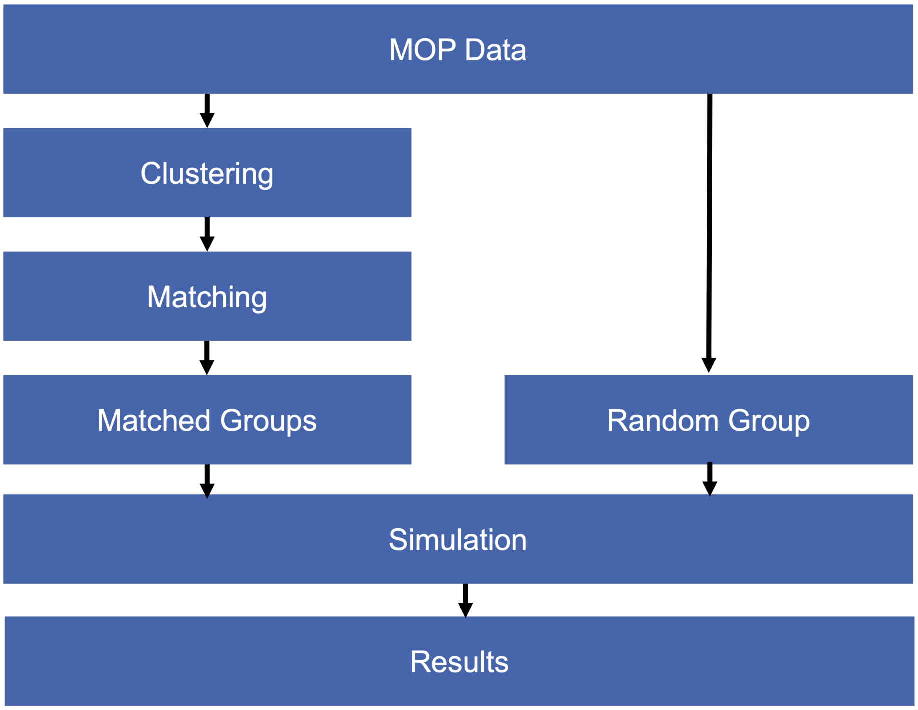

Figure 3.3.: Process for the Evaluation of Shared Private Charging Stations

3.3. Results

The output of the simulation allows for an evaluation of the general potential to share a private charging stations using random groups as well as the possibility to improve the fit using the matching algorithm. The results are presented in the following.

3.3.1. Matched Groups

Using the matching algorithm defined in Section 3.2.4, a total of seven sequences are identified, each with one of the clusters as the seed. An overview of all sequences is provided in Table 3.3.

The results show that the clusters are not selected equally often. The most frequent sub-sequence within the results is 134, which includes the clusters *High Frequent Commuter*, *Weekend trips* and *Frequent Local Errands*. It appears as if these patterns complement each other and are consequently frequently selected by the matching algorithm. Further, the results also indicate, that Cluster 5, 6 and 7 do not fit well with the others, as they are never selected besides the forced selection in Sequence

Table 3.3.: Overview of sequences identified by the matching algorithm

Seed Cluster	Sequence
1	134413413134122
2	234134134131341
3	314413413134134
4	441313413134134
5	5111111
6	63333131313
7	7441341313413

5, 6 and 7 at the beginning. This can be explained using the characteristics shown in Table 3.2. Cluster 5 and 6 are referred to as *Weekend High Mileage* and *Frequent High Mileage* and consequently require a large amount of energy to cover their trips. In addition, Cluster 7 *Seldom at Home* poses a challenge for home charging as the time available for recharging might not be sufficient.

3.3.2. Charging Strategies

In order to assess the quality of a group of EV users, the *share of distance covered from home* as well as the is energy *charged publicly* are used. Both the results of a random allocation of users to a private charging station as well as the allocation using the sequences shown in Table 3.3 are analyzed in the following.

The *share of distance covered from home* is defined as the ratio between the aggregated distance of all trips within a group and the distance covered using energy charged at the private charging station. A *share of distance covered from home* of 1 therefore describes a group that was able to cover all of its demand at the wallbox, which is the objective within this study. In Figure 3.4, the *share of distance covered from home* for the random as well as matched groups is shown for group sizes from one to 14 participants. To highlight the gap between the random and the matched groups, Figure 3.5 illustrates the difference in percentage points.

Overall, the results show that from a technical perspective, sharing a private charging station has great potential as even a random allocation allows users to accomplish between 77% and 89% of their trip distances. However, with respect to Research Question 1, the results show that even though users can expect a large share of their

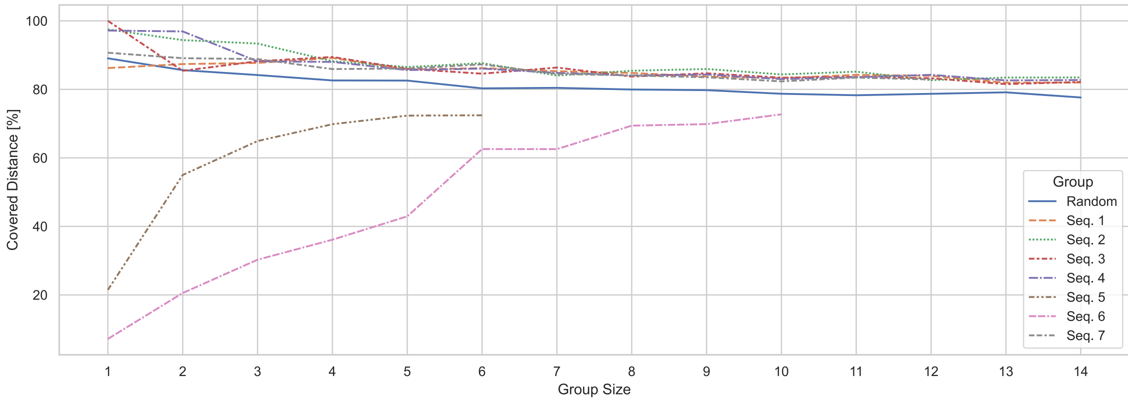

Figure 3.4.: Share of Distance Covered Using Only Home Charging

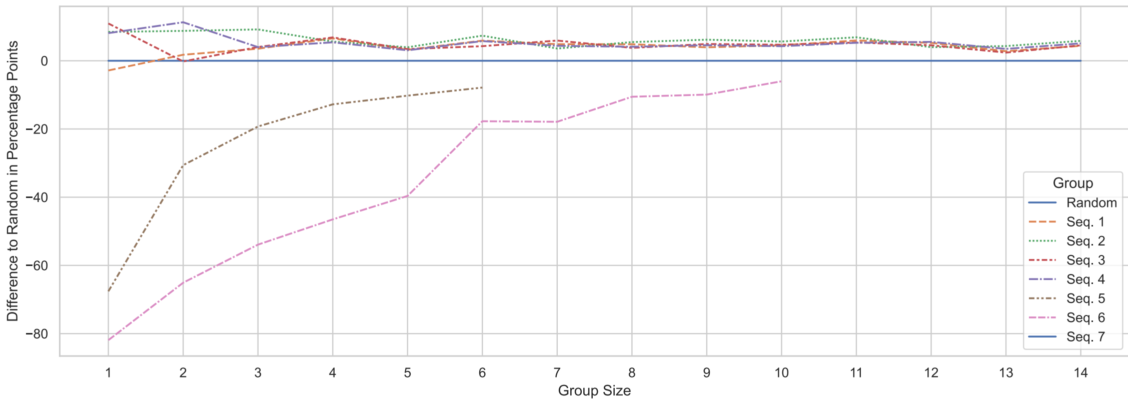

Figure 3.5.: Additional Distance Covered Using the Matching Algorithm

trip distance to be covered by energy charged at the shared wallbox, a coverage of 100% is not achievable. This is noticeable when looking at the results for a group size of 1. Here, the average expected *share of distance covered from home* for a member of each cluster is shown. Only members of Cluster 3 can expect to cover every trip if they purchase a private charging station but without sharing it. Notably, by increasing the number only to two group members, there is no group that is able to cover every trip, which causes an impact on the mobility patterns of the group members.

With respect to the matching algorithm, the results show that most identified matched groups outperform the random allocation. Especially with a smaller number of members in the group, there is a noticeable difference between the performance of the sequences. However, with an increasing group size, the results of the sequences converge. This might be due to the patterns of Clusters 1, 3 and 4 occurring within the sequences, as discussed in Section 3.3.1.

Nonetheless, there are also two sequences, that perform substantially worse than the random allocation. In Sequence 5 and 6, the *share of distance covered from home* increases with additional members in the group. The reason for this is the bad fit of Clusters 5 and 6 for private charging infrastructure. Due to their high distance traveled, both clusters rely on public charging stations to cover their demand. Thus, with increasing group sizes, Sequence 5 and 6 compensate for this behavior with members of the Cluster 1 and 3.

For an economical evaluation, it is further important to quantify the need to charge at public charging stations, which is shown in Figure 3.6. Similar to the results of the *share of distance covered from home*, Sequence 5 and 6 cannot utilize the private charging station to cover their demand but rather rely on public infrastructure. With an average of 220 to 326 kWh charged outside from home, Sequence 6 performs worst overall. For the other sequences, the demand for public charging is reduced when compared to a random allocation. Here, Sequence 2 has the best results with a range of 15 to 192 kWh charged outside from home.

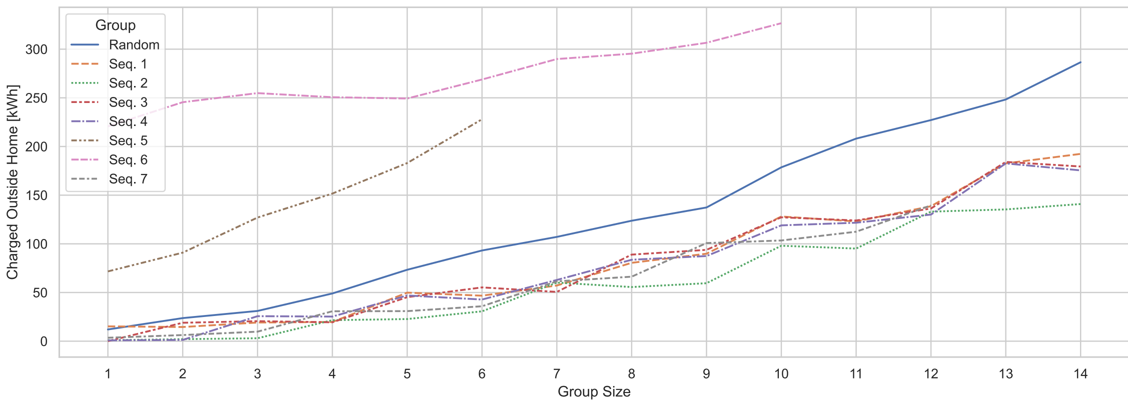

Figure 3.6.: Energy charged publicly

3.4. Discussion

The simulation and the matching algorithm introduced in this chapter follow assumptions on the behavior of users that are discussed in the following.

The basic assumption of this chapter is that users follow a similar pattern over time. The data set used provides empirical data of drivers within Germany for a complete week and it is assumed that users follow this pattern throughout the year. Special trips, such as going on vacation might not be represented in the data for every user, especially if multiple users of a group take a longer trip at the same time. The results therefore only provide insights on the general potential of users to share a private charging station, but cannot guarantee that the result can be achieved in practice.

Furthermore, the simulation assumes that users are able to determine the exact amount of energy they need to charge at public charging stations to cover their trip back home. In a real world setup, users might not be able to do so and might not want to charge the exact minimum at public charging stations, which can increase the amount of energy charged outside from home. The main objective of this chapter is to identify if sharing a private charging station is technically feasible for a given set of empirical mobility patterns. However, there is no evaluation of the actual charging location with regards to the possibility of starting a charging session even if there are other vehicles still parking at the wallbox. Due to the charging station being blocked by parking vehicles, some charging sessions can potentially not be initiated, reducing the potential benefit of sharing a wallbox.

Finally, the simulation focuses on the technical properties of sharing a wallbox. Even though the results show that users are able to share a wallbox with their neighbors, further research is required to ensure that users are willing to accept such a concept. When sharing a wallbox, users can experience situations in which they cannot instantly charge, which might hinder them from participating in such a sharing model. Furthermore, social factors such as the relationship between neighbors are not considered.

3.5. Conclusion

Within this chapter, the potential of sharing private charging stations in an urban setup is analyzed. To achieve this, in a first step, a total of seven user clusters with similar mobility patterns is identified. Using theses clusters, a novel matching algorithm is introduced that allows users with complementary mobility patterns to be matched into groups, that share a charging station at home. To quantify the impact of the matching algorithm as well as to answer Research Question 1, an agent based simulation is used to analyze the coherence of mobility patterns of the users within a group. Furthermore, these groups are benchmarked against a random selection of users.

Overall, the results show, that sharing a private charging station has great potential, since even with a random creation of a group, between 77% and 89% of their trip distances can be operated using the energy charged at home. Using the matching algorithm, this result can be improved even further. For users, the results demonstrate that sharing their wallbox with neighbors can provide benefits to the involved parties. Further, for practitioners the results demonstrate that there is a demand for bringing users together and matching them in a way that complements their mobility patterns.

Finally, the results show that not every mobility pattern is suitable for private charging. Even when the wallbox is not shared, some users are unable to follow their mobility patterns when switching from an ICEV to an EV. Especially when trips are longer than the range of a vehicle, charging at home is not sufficient to fulfil the complete mobility demand of users. Here, public charging stations are required, which are discussed in the following chapter.

Chapter 4.

User Behavior for Destination Charging

To extend the mobility of private EV users beyond the area surrounding their home, a broad network of public charging stations is needed. Some of these stations are located at the planned destinations of private EV users and allow them to charge their vehicle without the need for additional trips. This is referred to as public destination charging. The objective of this chapter is to emphasize the importance of such locations as well as to quantify the impact of user behavior on the users themselves as well as on the CPO. A framework is developed to determine the losses associated with user behavior and different scenarios are introduced to demonstrate the influence of user behavior within the framework. The findings of this chapter highlight the importance of considering user behavior in future research models for the siting of charging stations and to help CPOs to identify new locations for public destination charging. This chapter comprises the results of Schmidt et al. (2020) published in *Applied Energy* and is a joint work together with Philipp Staudt and Christof Weinhardt.

4.1. Introduction to Destination Charging

Whilst charging infrastructure cannot influence the range of a vehicle, it can increase the SOC at the beginning of a trip if the vehicle is plugged in. This requires charging infrastructure at locations close to the driver's parking spot. Additional trips to public charging infrastructure can be seen as an burden that needs to be minimized.

Several studies have already focused on optimal charging infrastructure localization in order to minimize additional trips (Sweda and Klabjan, 2011; Pan et al., 2017) or to reduce the walking distance to charging stations (Chen et al., 2013). In the scenario presented in this chapter, we define the optimal outcome as a charging infrastructure network where no additional trips are necessary as the energy charged at the destination of each trip is adequate to fulfill the next journey. This kind of charging is also referred to as destination charging.

The term “Destination Charging" is frequently used in literature and industry but definitions are rather rare and diverging. Tesla has a product called Destination Charging that allows Tesla drivers to charge their vehicle upon arrival at selected hotels, restaurants and shopping centers (Tesla, 2019). The authors of Zhang et al. (2016) define destination charging as charging sessions that happen after an EV arrives at its destination, including home and workplace charging. In the work of Dixon et al. (2018), destination charging is defined as charging sessions from 10 to 180 minutes at amenities such as supermarkets, gyms, cinemas and shopping centers, therefore excluding charging at home or at work. The authors of Haorui et al. (2018) follow Tesla’s differentiation between super- and destination charger and define the latter as charging at malls, hotels, residential communities and other public places, where parking is possible.

The definitions provided differ mainly in two aspects: First, the destinations covered may either only include public locations or can be extended to charging at home or work. The second aspect focuses on the time spent for charging. Whilst most definitions do not include a time limit, there are definitions providing an upper and lower bound. In addition, none of the definitions considers the customer’s need for charging. Given the partly contradicting use of the term destination charging in literature and the missing focus on user behavior, this chapter proposes a new, more detailed definition:

Definition Destination charging describes the charging of electric vehicles in places where the need for parking is independent of the state of charge of the vehicle. The primary aim of the driver is reaching and parking at a destination whereas charging can be considered an on-top service.

Possible destinations are hotels, supermarkets or gyms, but also home or work. Since the latter two are private and semi-public, they differ in their usage. In this chapter, we focus on locations that are public, which is referred to as *public destination charging*. Charging sessions not covered by the term destination charging are those where EV drivers charge in the middle of a trip to extend their range, for example, at rest stops close to the highway. This kind of charging is also referred to as urgent charging (Zhang et al., 2016) and is not covered in this chapter.

The definition of destination charging proposed in this chapter extends current literature with a new view on parking and charging at a location. It implies that the process of parking can be seen as being controlled exogenously by the necessity of a trip for a specific activity. Therefore, the charging session at the parking destination has to occur within the boundaries set by this activity. In contrast to recent literature, this definition of destination charging clarifies that a user's decision to park is independent of the availability of charging stations. As charging is independent of the stay at a location, drivers will not need to queue in front of charging stations or return to their vehicle early in order to start a charging session. As a consequence, we show that it is essential to consider user behavior at a location to both provide customers with the appropriate charging infrastructure as well as to ensure an economic operation of charging infrastructure in the context of public destination charging.

In this chapter, we focus on the influence of user behavior at a specific location on the revenue of the charging stations by determining the demand of EVs covered. We show that aggregating the demand of all vehicles arriving at the location is not an adequate estimator for revenue of the charging infrastructure as occupied charging stations and early departures are not considered.

We also show how different user behavior influences the expected revenue and present a case study to illustrate the effect of user behavior on the expected revenue of charging infrastructure located at supermarkets.

The contribution of this chapter towards answering Research Question 2 is split into the following three sub-questions:

RQ 2.1 What is the impact of user behavior on the economic evaluation of public destination charging locations?

RQ 2.2 How does user behaviour affect the covered demand of users and how can charging station operators control this indicator?

RQ 2.3 What is the impact of user behavior on the evaluation of supermarkets for public destination charging?

4.2. Related work

Optimal siting of electric vehicle charging infrastructure is one of the key drivers for EV adoption and is extensively analyzed in the literature. In addition to a wide variety in underlying data, assumptions on drivers charging behavior and future EV adoption, researchers also consider a spectrum of objectives when siting charging stations. In this section, we focus on the different approaches to evaluate the location of charging stations and their fit for destination charging. The papers are grouped by their main objective.

Welfare One method to determine the optimal location for charging stations is to optimize the welfare of the whole system. The authors of (Luo et al., 2018) determine the optimal location for charging infrastructure by minimizing the social cost of the whole charging system. They define social cost as the aggregation of annual investment and O&M cost for charging stations, annualized grid reinforcement cost and annual network losses cost. Their evaluation is based on eight typical days over a year and parking behavior is aggregated in three different scenarios. User behavior at a particular location is neglected. The authors of (He et al., 2013) site a given number of public charging stations to maximize social welfare for an average hour. The social welfare includes the expected utility and the charging expenses of the driver, the total generation cost of electricity and the total construction cost for the charging network. By looking at an average hour, consequences through different utilization of the charging station during the week are not covered.

Convenience One of the advantages of destination charging is its ability to blend into EV owners' mobility pattern without the need for additional trips for charging. As charging or specifically limited access to charging stations causes an inconvenience to the driver, several studies minimize additional effort to charge the vehicle. Effort can be expressed through the additional trips needed for charging or the additional distance driven. The authors of (Chen et al., 2013) propose a parking based assignment method that minimizes EV users' station access cost, defined as the walking distance from the charging station to the driver's ultimate destination zone, while penalizing unmet demand. By looking at parcels, information on the actual location of the destination was not included. In (Guo et al., 2018), the authors optimize the convenience of EV drivers by considering the range anxiety in the charging station location problem. Even though both papers presented in this paragraph follow the general idea of destination charging, which is to provide a convenient location for charging an EV, they both lack a detailed consideration of user behavior at the location.

Covered demand Another similar approach for siting charging stations is to maximize the demand of EVs arriving at a location covered by a provided infrastructure and thereby to maximize the electrically driven distance. Here, destination charging is a tool to cover additional demand without a change in the mobility pattern of EV owners. The authors of (Frade et al., 2011) maximize the covered demand for a given number of charging stations in the city of Lisbon. By applying a fixed time of 6 hours to charge a vehicle for every location, individual information on the stay of EV owners is not considered. In (Asamer et al., 2016), the authors position charging stations in Vienna to satisfy the charging demand of electric taxis and therefore maximize the sum of covered taxi trips. They focus on regions with a demand for charging stations rather than an exact location. The authors of (Shahraki et al., 2015) analyze travel patterns of taxis in Beijing and minimize the total travel distance that cannot be fulfilled using electricity. The latter two paper focus on commercial fleets and therefore do not account for user behavior. In (Andrenacci et al., 2016), a demand-side approach is used to identify optimal location zones for charging infrastructure based on aggregated demand. An analysis whether this demand can be covered due to blocked charging stations is not conducted. The authors of (Arias et al., 2017) propose a time-spacial demand forecast model in urban areas where the patterns of various charging stations are analyzed. Their assumption that customers will queue in front of a charging station and leave immediately after charging their batteries hinders a direct application in the context of destination charging.

Literature in the field of covered demand is closely related to the objective of destination charging, which is to supply energy to customers at a location connected to their mobility pattern. Nevertheless, literature on the behavior of customers at particular types of destinations is rare and needs further investigation.

Grid integration Other studies focus on a grid compatible location for charging infrastructure. A grid compatible roll-out of destination charging stations is necessary to ensure a sustainable expansion of the charging network. The authors of (Khalkhali et al., 2015) determine the optimal location of charging stations by maximizing the distribution system manager benefit. They consider both the value of appropriate charging and discharging of EVs and use EVs to provide spinning reserve and supply the electricity network's load at peak times. In (Staudt et al., 2018), the authors show how V2G-enabled charging can reduce the cost for redispatch in Germany. With a focus on bi-directional charging of EVs, there is still a need to include the charging demand of a particular destination and the user behavior connected to it.

Cost efficiency As the initial investment in charging infrastructure is high, numerous studies focus on an economical distribution of charging stations. The authors of (Xiang et al., 2016) construct a cost based model where the minimum total cost is determined as the sum of the annual investment for charging stations, the annual operation cost of the substation and the cost for power losses. By assuming a random arrival time of EVs and a queue in front of the charging station, this approach is insufficient in the context of destination charging as defined in this chapter. In (Ip et al., 2010), the authors calculate a cost efficient charging infrastructure for a given demand by minimizing the operational costs. By determining demand clusters and assigning charging stations, it remains unknown how and if this potential demand can be met when user behavior is considered. The necessary utilization needed for a profitable operation of charging stations is analyzed in (Wirges et al., 2012) for the region of Stuttgart, Germany. Similar to the previous paper, the authors assume that the potential demand can be met by assigning charging stations without considering when EV owners arrive and how long they stay at a location. Trips from a household travel survey are used in (Baouche et al., 2014) for the localization of charging infrastructure. The objective here is to minimize the charging station's fixed cost and the EV travel cost for a given set of candidate locations. Various costs are considered in (Liu et al., 2013) including the investment cost, operation cost, maintenance cost and network loss cost to minimize the total cost associated with EV charging. The results show, that the approach is not only suitable for planning the location of EV charging stations, but also reduces the network loss and improves the voltage profile in the considered use case. Neither of the previous two papers include a temporal consideration of the demand at a charging station. Therefore, it remains unclear whether the potential demand at a location can be met when considering user behavior for destination charging.

Contradicting objectives To accommodate for partly contradicting objectives while constructing charging infrastructure, researchers use multi-criteria decision-making methods. This also applies to destination charging as locations with a high number of potential customers are not necessarily the cheapest destinations to operate. The authors of (Guo and Zhao, 2015) maximize sustainability of charging stations, which consists of environmental, economic and social criteria to rank potential locations in the Changping district in Beijing, China. The model of (Guo and Zhao, 2015) is extended in (Ju et al., 2018) with an additional focus on technological criteria. The framework is employed to determine the best out of six pre-selected sites in Beijing. In (Cui et al., 2018), the authors follow a similar categorization approach and define criteria based on economic, social and environmental factors as well as engineering feasibility. All of the papers presented in this paragraph do not account for the characteristics of destination charging. There is a need to include the behavior of customers to provide a more detailed assessment of the usage of charging stations.

Besides their different optimization goals and considered input parameters, these frameworks and models also differ in the concreteness of the charging station's location. The papers can be categorized into region based and location based approaches. Region based approaches do not define the exact location of an individual charging station but rather determine the number of charging stations needed in a predetermined region or area. Such regions can be urban districts (e.g., Pan et al. (2017); Wirges et al. (2012)) or a grid placed over a given map (e.g., Ip et al. (2010); Dong et al. (2014); Namdeo et al. (2014)). In comparison, location based approaches determine the exact location of a charging station from either a given set of possible locations (e.g., Frade et al. (2011); Gharbaoui et al. (2013); Genevois and Kocaman (2018)) or within an analyzed area (e.g., Guo and Zhao (2015)).

The approach developed in this work belongs to the latter category. In the context of destination charging, the exact location of a charging station is necessary as user behavior is connected to a particular location. Region based approaches cannot incorporate the user behavior and assume that drivers of EVs will adapt their mobility pattern to charge at the supplied charging infrastructure.

However, in the context of location based approaches, as shown in this section, user behavior is mostly neglected. Most approaches focus on a potential demand for charging infrastructure but do not evaluate whether this demand can be met based on drivers' arrival at a location and length of stay. Therefore, this chapter addresses this issue by investigating to what extent a potential demand can be met when user behavior at a location is considered. Different scenarios are analyzed to examine the influence of different parameters of user behavior on the demand covered for a given location.

The approach described in this chapter follows the perspective of demand covered as the main goal is to maximize the energy charged at the charging station by identifying locations with a user behavior that supports public destination charging. In addition, this approach also considers the perspective of convenience as user behavior is assumed to be fixed. Drivers of EVs do not need to adapt their mobility pattern and have the additional benefit of charging their EV at their destination.

4.3. User behavior model

This section covers the theoretical foundations necessary to determine the demand of potential customers covered, the losses connected to user behavior as well as the setup of the simulation.

4.3.1. Demand and losses

As a charging station operator, it is important to predict the energy sold at a potential location. In this section, we start by looking at the characteristics and aggregated demand of EV owners and then demonstrate how potential demand can be lost due to user behavior. The objective of the approach is to emulate user behavior at a given destination over a full week and to implement it as an agent based Monte Carlo simulation. Each agent $i \in [1, \ldots, n]$ represents a single EV driver and is characterized by an arrival time a_i, a dwell time s_i and a demand d_i for energy. The demand, as defined in this chapter, does not necessarily represent the energy needed to reach an SOC of 100% but rather the energy required to get to the next destination charger. In the case study discussed in Section 4.5, for example, demand refers to the amount of energy needed to cover the average mobility needs between each stay at a supermarket. The variable n defines the total number of arrivals at a location. At the analyzed destination, each charging station $c \in [1, \ldots, m]$ has a maximum charging speed of p_c. We acknowledge that the actual charging power is both determined by the charging station and the vehicle. For the purpose of this research, we assume the charging station to be the bottleneck.

This approach can be seen as an extension to existing charging station positioning models as it is based on a potential demand for charging infrastructure at a destination. Potential demand D_{pot} is defined as the sum of the demand of all agents arriving at the destination:

$$D_{pot} = \sum_{i=1}^{n} d_i \tag{4.1}$$

The potential demand can be seen as an upper bound for the energy a charging station operator could sell to EV owners at a location. In contrast to current literature, the focus of this model is to analyze the impact of user behavior on D_{pot} by quantifying the losses determined by the arrival and dwell times of customers as well as other contributing parameters. Therefore, this approach can be used to assess whether the anticipated potential demand can be met with a given charging infrastructure and a given specific user behavior.

Losses occur in two stages of the charging process. The first stage takes place at the arrival of an agent at the destination. As charging is considered an additional service in the context of destination charging, a customer will not queue in front of an occupied charger. Therefore, she will park at a spot without charging infrastructure instead and the demand remains unmet. D_{cha} defines the total demand of all charging sessions actually served. The loss of revenue in this stage is referred to as Occupancy Loss (OL) and describes the discrepancy between D_{pot} and D_{cha}.

$$D_{cha} = \sum_{i=1}^{n} \mathbb{1}(i) \cdot d_i \tag{4.2}$$

$$\mathbb{1}(i) = \begin{cases} 1 & \text{if agent i finds a charging station} \\ 0 & \text{else} \end{cases} \tag{4.3}$$

The second stage of losses occurs at the end of a charging session. The dwell time of agents is assumed to be independent of the charging demand. Their behavior depends on the activity at the destination and not the charging process. Therefore, agents will leave the destination as soon as their objective of the stay is fulfilled. A loss occurs if the dwell time is not sufficient to meet the demand of the agent. This can be caused either by a too short stay or a slow charging speed and is referred to as Early Departure Loss (EDL). This loss is especially relevant in the context of destination charging as EV drivers prefer to fully charge their vehicle in urban areas (Luo et al., 2018). Therefore, an early departure represents an inconvenience from both a customers as well as a charging station operator's perspective. The actual demand covered D_{cov} is calculated by determining the minimum of the agents demand and the energy she is able to charge during her stay and represents the basis for revenue of the charging station operator.

$$D_{cov} = \sum_{i=1}^{n} \mathbb{1}(i) \cdot \min\{d_i, s_i \cdot p_i\} \tag{4.4}$$

$$\mathbb{1}(i) = \begin{cases} 1 & \text{if agent i finds a charging station} \\ 0 & \text{else} \end{cases} \tag{4.5}$$

The losses considered in this model are illustrated in Fig. 4.1. The overall goal of the approach is to analyze and quantify the losses from D_{pot} to D_{cov} and how user behavior influences these losses.

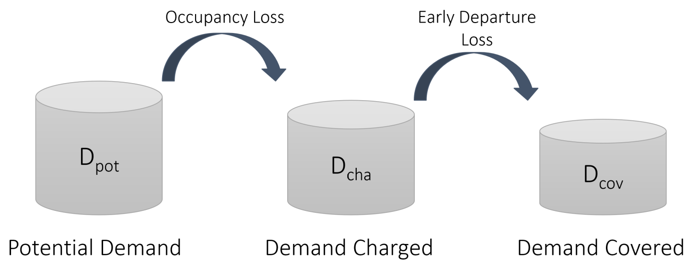

Figure 4.1.: Losses in demand due to user behavior

4.3.2. Simulation

To this end, a simulation is implemented that replicates the agents' behavior for one particular destination. Each run of the simulation iterates over every minute of a week and determines the number of EVs arriving at the destination. In case they are available, the EVs are allocated to one of the charging stations. Otherwise, the agent is parked at a standard parking lot and is not further considered. The simulation then assigns a dwell time and demand to the agent and initiates the charging session. Once the dwell time has passed, the agent leaves the charging station and allows new agents to cover their demand. As the number of arrivals, the dwell time and the demand of an agent can be stochastic, the simulation follows a Monte Carlo approach. In addition, this allows including random utilization patterns. All the results presented in this chapter are based on 1000 runs and the different levels of demand and the losses connected to user behavior are both determined as the arithmetic mean.

4.4. Evaluation

In this section, we evaluate different scenarios and combinations of input parameters to gain insights into the influence of user behavior on the demand covered at a destination. The section focuses on two categories of input parameters. On the one hand, the influence of the location specific variables such as arrival time, dwell time, the total number of arrivals as well as the demand are analyzed. These variables characterize a given destination and cannot be influenced by the charging station operator. On the other hand, charging station operators can adjust the infrastructure provided by increasing the number and power of charging stations. These parameters represent the second category called infrastructure specific variables. Therefore, the influence of user behavior and the associated losses as well as possible infrastructure based countermeasures are analyzed.

4.4.1. Basic scenario

Modeling user behavior for destination charging requires a few assumptions and allows multiple possible combinations of different parameters. In the following, we configure the base scenario of a destination representing an exemplary supermarket as a benchmark. We assume that 100 EVs arrive at the destination each day which adds up to 700 EVs per week. We assume a constant number of customers inside the store over a full day with an up ramping phase in the morning and a down ramping phase in the evening. Both periods are 2 hours long and reduce or increase the utilization linearly. The supermarkets opens at 10 am and closes at 8 pm. This utilization pattern is referred to as pattern 1 and is illustrated in Fig. 4.2. The algorithm to extract the arrival times of agents for a given utilization pattern is given in Section 4.4.2. The typical dwell time is set to 20 minutes. On average, German customers visit a supermarket 3 times per week (Splendid Research GmbH, 2016). This matches the typical charging pattern of today's EV driver. The authors of (Schäuble et al., 2017) find that EVs are charged every third or fourth day. In (Franke and Krems, 2013), the authors find that EVs are charged three times a week. With an average weekly mileage of 205.8km per person (Eisenmann et al.), this results in about 69.6km between each visit of a supermarket. As we assume that destination charging is especially convenient for EV drivers without the possibility to charge at home, we analyze the case in which drivers try to meet their total demand at supermarkets. With a typical consumption of 0.2 kWh per km (Flath et al., 2012), this results in an average demand of 13.72 kWh per arrival. Charging stations constructed at supermarkets in Germany usually have a charging rate of 50kW (Jeß and Hänsch-Petersen, 2019). Therefore, we adopt this for the base scenario. The number of charging stations is set to 4. We expect that EVs are capable of utilizing the full power of 50kW over a full charging session and neglect a ramp-up in power or limitations due to cold batteries. An overview of the parameters of the basic

Parameter	Basic Scenario
Arrival Time	Pattern 1
Dwell Time	20 minutes
Demand	13.72 kWh
Arrivals Per Week	700
Charging Stations	4
Charging Power	50 kW

Table 4.1.: Basic Scenario

scenario is given in Table 4.1.

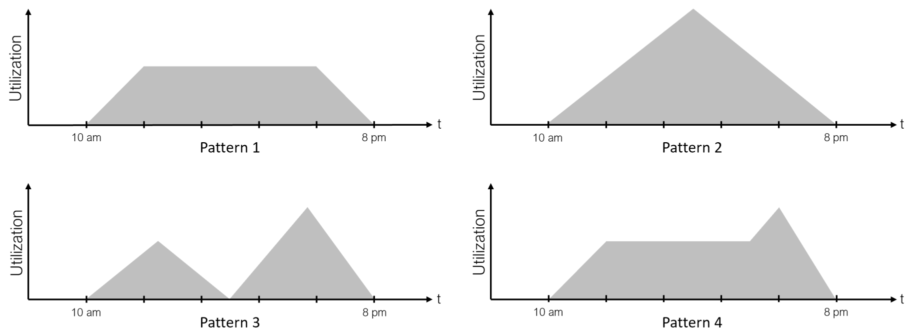

Figure 4.2.: Overview utilization pattern

4.4.2. Extraction of the arrival time

Information on the exact arrival time of customers is rare and even if stores track it, they do not make the information available. In this chapter, we approximate the arrival time based on a given utilization using a Monte Carlo approach. The basic idea is to iterate over each time step $t \in T$ of the utilization pattern and reconstruct the original utilization rate using charging sessions generated with a predetermined dwell time. The Monte Carlo approach is chosen because dwell time can be stochastic and therefore, a single application of the algorithm can lead to inadequate results. The process is described in Algorithm 1, where dwell time is assumed to be uniformly distributed between the $minDwellTime$ and $maxDwellTime$. Other distributions might be included in future work. The $utilizationPattern$ describes the original pattern and the $arrivalPattern$ describes the approximated number of arrivals for each time slot. The analysis in this chapter is based on 1000 runs to extract the arrival time.

Algorithm 1: Arrival Approximation

Input: usagePattern, minDwellTime, maxDwellTime, runs
Output: arrivalPattern

$usageApproximation = [0] \cdot length(usagePattern)$
for *r in range(runs)* **do**
  for *i in length(usagePattern)* **do**
    while $usagePattern[i] > usageApproximation[i]$ **do**
      for *j in range(randomInt(minDwellTime, maxDwellTime))* **do**
        $usageApproximation[i + j] += 1$
      $arrivalPattern[i] += 1$
$arrivalPattern = arrivalPattern/runs$
return *arrivalPattern*

The advantage of this algorithm is its flexibility to integrate different distributions of dwell time as well as random utilization patterns.

4.4.3. Influence of user behavior on losses

In this section, we analyze the influence of user behavior on the demand covered and the incurring losses. We do this by varying the dwell and arrival time as well as the demand of the agents.

Dwell time

The dwell time s_i of agent i at the destination influences both the OL as well as the EDL. If agents have a long dwell time at the destination, it increases the possibility of subsequent agents to find all charging stations blocked on arrival. Nevertheless, a long dwell time allows the agent to charge more and therefore the EDL is reduced. This trade-off is analyzed in this subsection. In each scenario, the dwell time is increased by a minute and the scenario is labeled as S_x where x represents the dwell time of each agent in minutes. The results are illustrated in Fig. 4.3. As expected, the OL increases and EDL decreases with a longer dwell time of the agents. For a dwell time smaller than 16 minutes, the decrease in EDL exceeds the increase in OL and therefore, the overall losses drop to a minimum of 20% of the potential demand. With a dwell time larger than 16 minutes, there is no EDL and the loss is fully determined by the OL. The analysis of dwell time highlights the problem when using potential demand as a quality measure for destination charging as currently done in literature (e.g. (Wirges et al., 2012; Frade et al., 2011; Asamer et al., 2016)). When looking at the potential demand only, all scenarios score the same. However, by including the user behavior, one can see that the demand covered and therefore, the potential revenue varies drastically. In addition, the analysis shows that both destinations with a very short or long dwell time are characterized by great losses caused by different effects.

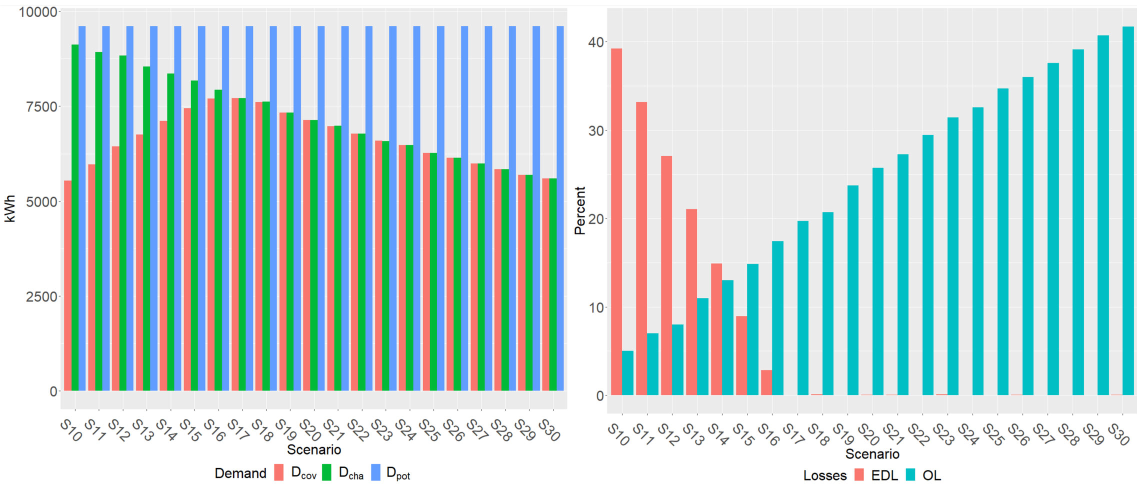

Figure 4.3.: Losses in demand due to user behavior for varied dwell times

Arrival time

The OL is not only determined by the dwell time of the agents but also their arrival time. As mentioned in Section 4.4.2, information on the arrival time of customers is rare and not available on a large scale. Therefore, we focus on the utilization of destinations as an intermediate step to derive the arrival time. In this subsection, we extract the arrival time of agents based on self-defined patterns of the degree of capacity utilization at the destination. Each pattern covers the same period from 10 am to 8 pm and distributes the same number of agents. Pattern 1 represents a destination with a constant degree of utilization as described in Section 4.4.1. This pattern can be found at destinations where customers need appointments like authorities or the doctor's office. The second pattern describes destinations with a peak utilization during the middle of the opening hours. Utilization increases linearly before and decreases linearly after the peak. Destinations with this pattern are for example public swimming pools or zoos. Pattern 3 is characterized by two peaks and can be seen as a sequence of pattern 2 where the second peak is 50% higher than the first. This kind of pattern is characteristic for destinations that offer food like restaurants where customers have lunch (first peak) and dinner (second peak). The fourth and last pattern exhibits the same utilization as pattern 1 with an additional peak in the end. The peak utilization is 50% higher than the typical utilization for the day. This utilization pattern can be found at supermarkets where many customers shop throughout the day and a peak occurs when additional customers arrive on their way home from work. An illustration of all patterns can be found in Fig. 4.2. The patterns where constructed for the chapter and are not based on empirical data. In addition, the patterns do not cover the entirety but rather a selection of utilization patterns. They are intended to represent specific locations and are sufficient for the purpose of this section, which is to show the impact of different utilization patterns on the demand covered. Based on these patterns, the arrival times of agents are extracted using the algorithm described in 4.4.2. The corresponding scenarios are labeled P_x where x represents the pattern analyzed.

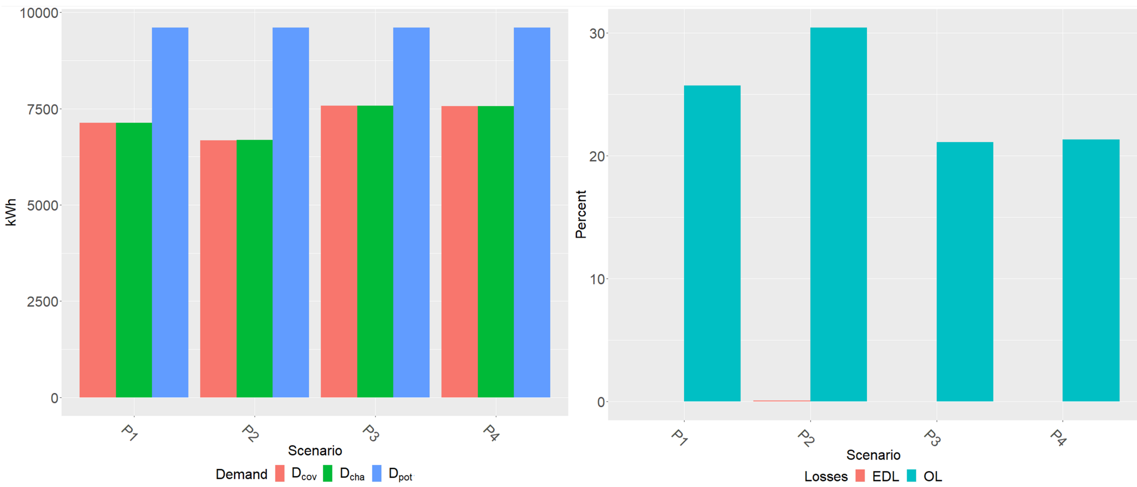

Figure 4.4.: Losses in demand due to user behavior for varied arrival times

The results show that there is a margin of almost 1,000 kWh when comparing the best and the worst pattern. Pattern 1 shows a medium performance with a D_{cov} of 7,132 kWh. The advantage of this pattern is the even distribution over the day. The lower results in comparison to pattern 3 and 4 can be explained by looking at the first and last 2 hours of the day. The slow change in utilization results in an under-utilization of the charging stations in the morning and evening, which cannot be compensated during the day. This also applies to pattern 2. Here, the charging stations are under-utilized in the morning and evening and overcrowded during the middle of the day. As a result, the OL is the highest over all patterns. Pattern 3 profits from a step-wise increase of utilization in the morning and afternoon. Due to the two peaks, the maximum utilization is lower compared to pattern 2, which results in a lower OL. Pattern 4 is similar to pattern 1 except for an additional peak in the evening. This reduces the under-utilization in the evening and leads to a higher D_{cov} compared to pattern 1.

This simulation of different arrival patterns allows for two insights into the profitability evaluation of charging destinations. First, an even distribution over the day can reduce the OL. This can be seen from the results for patterns 1 and 4. Second, the results also show that a steep increase in utilization can reduce the under-utilization in the morning and evening. This implies that a good location for destination charging should be characterized by a steep increase in utilization and an even distribution over the day.

Demand

The demand d_i describes the kWh an agent i wants to charge upon arrival. With an increasing demand, the time to charge rises and the stay at the destination might not be sufficient anymore. We analyze a sequence of scenarios, where the demand of each agent is successively increased from 3 to 22 kWh. The scenarios are labeled D_x where x represents the demand of the agents in kWh. The losses are illustrated in Fig. 4.5. Because the arrival and dwell times are equal for all scenarios, the OL is also the same. In addition, in scenarios with a demand smaller than 17 kWh, there is no EDL as the charge rate is sufficient to cover the entire demand of the agents. For a demand greater than 17 kWh, the EDL increases linearly. On the demand side, this results in a linear increase of D_{cha} and D_{cov} for an EDL of zero and a constant D_{cov}, thereafter. This is due to the fact that EVs charge the entire time they are located at the destination and additional demand cannot be covered by the given infrastructure.

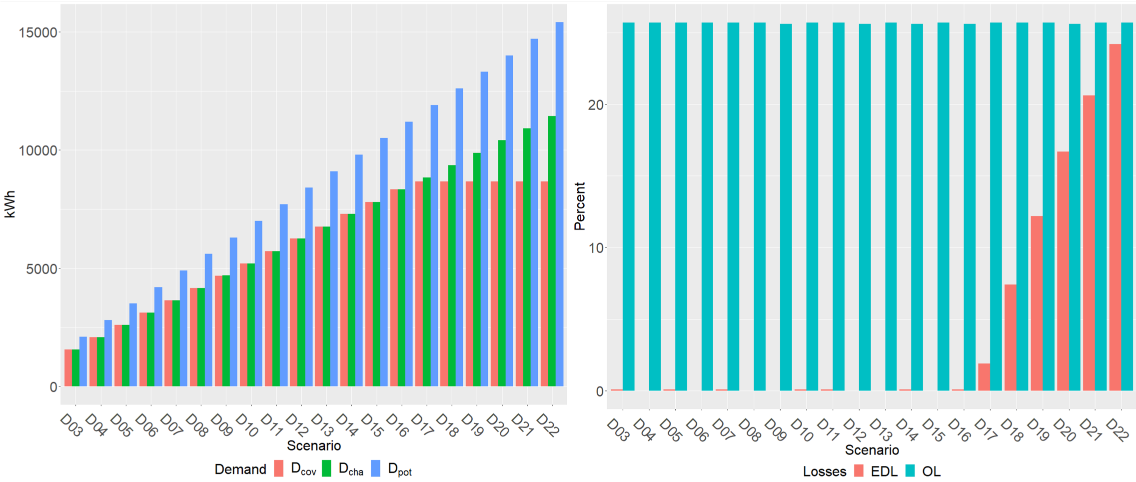

Figure 4.5.: Losses in demand due to user behavior for varied agent demand

Number of arrivals

The number of arrivals per week is not directly linked to user behavior but rather popularity and size of the destination. Nevertheless, combined with the arrival pattern, it determines the number of customers arriving at the destination in each time slot. Therefore, the number of arrivals per week has an influence on the availability of charging stations and the OL. In the following, we analyze the scenarios A_x where x represents the number of arrivals per week. The results are illustrated in Fig. 4.6. D_{pot} increases linearly with the number of arrivals. This is not the case for both D_{cha} and D_{cov} due to an increasing OL. With more than 1,300 EVs arriving at the destination in scenario A_{1300}, almost half of the potential demand is lost due to occupied chargers. As there is no EDL in this scenario, D_{cha} and D_{cov} are the same for all scenarios covered in this section.

4.4.4. Influencing losses

This section focuses on the possibilities to counter the losses caused by user behavior. Charging station operators have the possibility to do this by increasing the power of

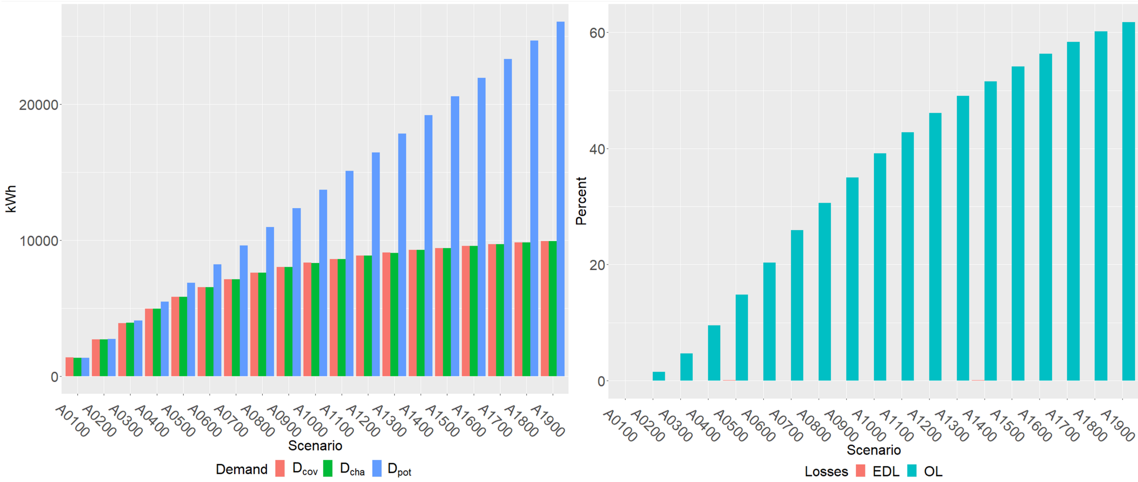

Figure 4.6.: Losses in demand due to user behavior for varied number of arrivals

each charging station or the number of charging stations.

Charging speed

The charging speed p_i determines the time needed to cover the demand d_i of an agent i and therefore has the potential to reduce the EDL. We assume that future EVs are capable of charging at more than 100kW (e.g. the Tesla Model 3 (250kW) (Blanco, 2019)). In the context of destination charging, charging speed is not as important as it is for charging at the highway. Therefore, we consider charging infrastructure with a power output between 10 and 100kW per station. As a consequence, it is likely that the limiting factor for charging the EVs is the charging infrastructure at the destination. We label the scenarios as C_x, where x represents the charging capacity in kW. The results are given in Fig. 4.7. The charging speed has no influence on the OL. This is due to the fact that according to the definition of destination charging, the agent's dwell time is not influenced by the SOC of the vehicle. Therefore, arrival and dwell time is the same in each scenario. The EDL is reduced with increasing charging speed and is reduced to zero for $p_i > 40kW$. The analysis shows that operators of charging stations have the possibility to reach D_{cha} by increasing the charging speed but not D_{pot}. In addition, the results demonstrate that from a charging station operator's point of view, there is no need to provide customers the highest charging speed for a given user behavior as lower charging speed is sufficient to cover the demand.

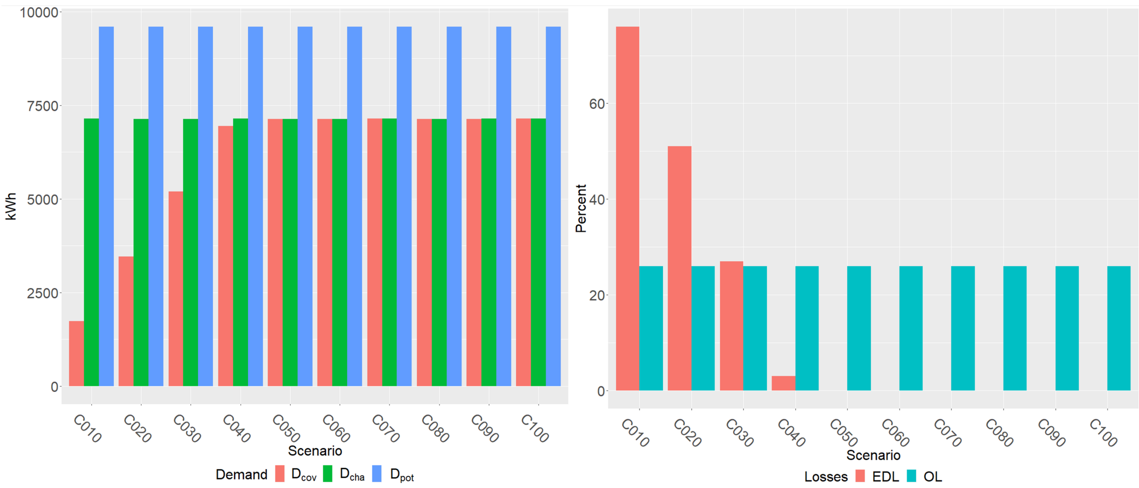

Figure 4.7.: Losses in demand due to user behavior for varied charging power

Number of charging stations

The number of charging stations installed at a destination influences the probability of finding an unoccupied charging station but also increases the cost of the infrastructure. We therefore analyze 10 scenarios labeled N_x where x represents the number of charging stations at the destination. As 50kW is sufficient to charge 13.72kWh in 20 minutes, there is no EDL in all scenarios analyzed. In addition, with an increasing number of charging stations, the OL also converges towards zero and the resulting D_{cov} converges towards D_{pot}. This shows that a sold quantity equal to D_{pot} is possible if both the charging speed and number of charging stations are sufficient. The question remains whether charging infrastructure with these characteristics is economical. This is not considered in this chapter but is a subject for future research. The results show that the marginal benefit of each additional charging station decreases.

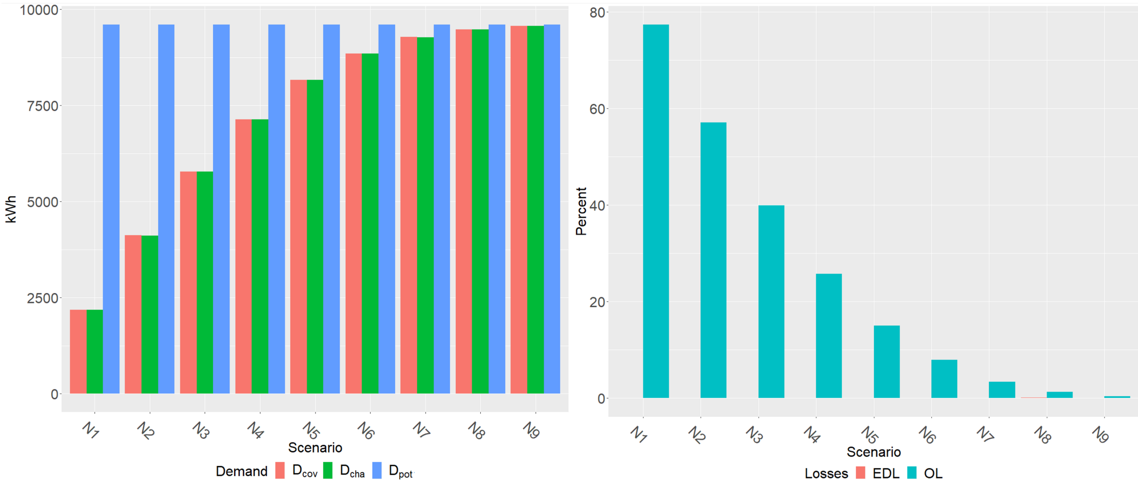

Figure 4.8.: Losses in demand due to user behavior for a varied number of charging stations

4.4.5. Trade-Off between number of arrivals and charging stations

The analysis shows that with an increasing number of EVs arriving at a destination, the charging infrastructure reaches its limits and is not able to handle the additional EVs. As a consequence, D_{cha} converges and the OL dominates the overall losses. However, more charging stations allow the charging station operator to harvest more of the potential demand up to a point where almost every customer is covered. In combination with an adequate charging speed, it is possible to cover the full potential demand. As comprehensive information about the absolute number of EV arrivals at a particular destination is not available and due to the increased market penetration of EVs, it is important to know if this information is essential to identify promising charging destinations. We therefore analyze every possible combination of charging stations within a range of 1 to 9 and the number of arrivals between 200 and 1000 in steps of 100 EVs. The results are illustrated in Fig. 4.9. As expected, total losses increase with an increasing number of arrivals and decreasing number of charging stations. The trade-off illustrated is especially important for charging station operators applying the findings of Section 4.4. Losses can be interpreted as an indicator for service quality and the number of charging stations are connected to the investment costs. Hence, this information can be used to approximate the investment needed to provide desired service quality to the customers. In addition, Figure 4.9 shows that overall losses due to user behavior stay the same if charging infrastructure is extended with increasing arrivals. This is important for charging station operators seeking to keep their service quality constant with an increasing number of EVs on the road. Consequently, the results indicate that knowledge about the absolute number of arrivals is not required to identify destinations with a promising user behavior as charging station operators have the possibility to adjust the service quality by increasing the number of charging stations. This is determined by the introduced factors.

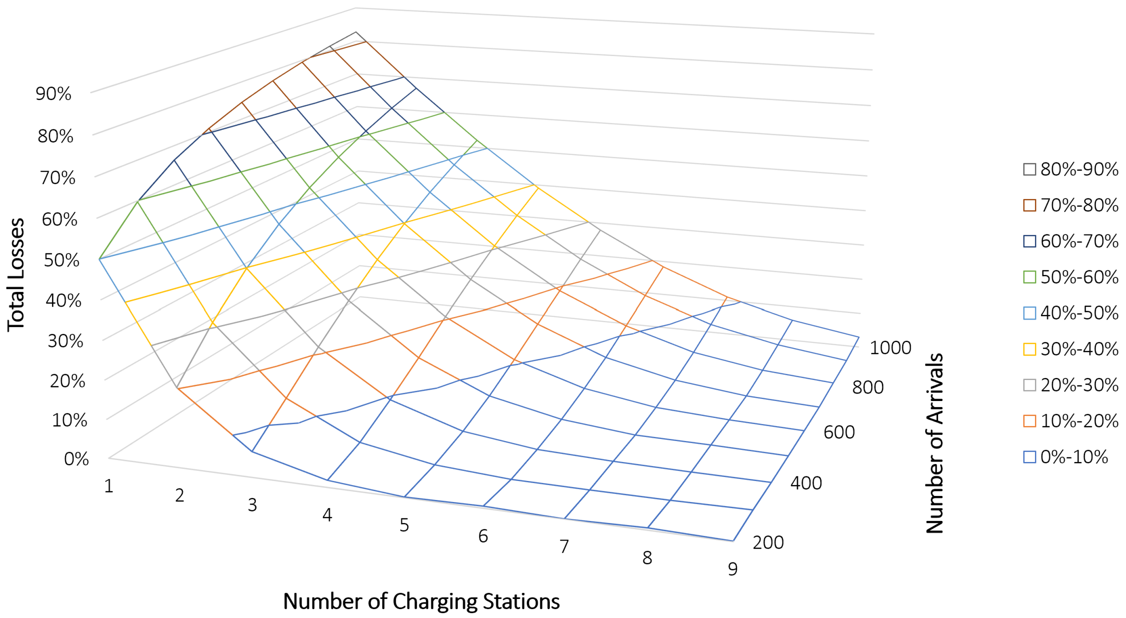

Figure 4.9.: Trade-Off between number of arrivals and charging stations

4.4.6. Overview of the losses and countermeasures

In this section, we have shown how user behavior influences the potential demand and the losses associated with it. An overview of the parameters and their influences is given in Fig. 4.10. Parameters can either influence only one loss, e.g. the arrival time only has an impact on OL, or both, like the dwell time. When looking at the countermeasures, one can see that increasing the number of charging stations allows to reduce OL and therefore, it is possible to build an infrastructure where D_{pot} equals

D_{cha}. To reduce EDL, a higher charging power is needed. Only if both, the number of charging stations and the charging power are sufficient, a destination charging infrastructure is capable to process the full potential demand. In all other cases user behavior and the losses associated with it have to be considered. Whilst this section focuses on the influence of a single parameter, it is also important to analyze how different combinations perform. This is done in the next section by looking at the user behavior at actual supermarkets.

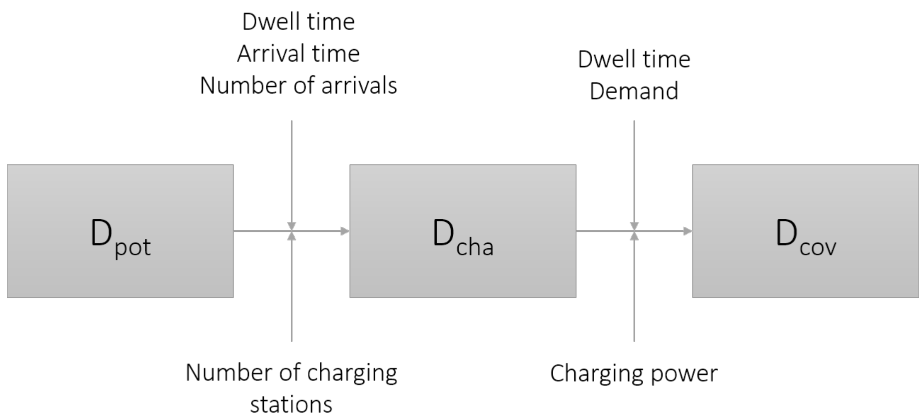

Figure 4.10.: Overview of the influence of parameters and countermeasures

4.5. Case study

In this case study, we demonstrate an application of our presented analysis. The aim of this section is to highlight the importance of considering user behavior when evaluating potential new locations for destination charging. Every destination has the same potential demand D_{pot} as we assume the demand of each agent and the total number of arrivals to be identical. We choose different supermarkets as potential destinations, which usually would be assumed to be similar with regards to their characteristics as charging destinations. Within the domain of supermarkets, we demonstrate the impact of user behavior on the charged energy amount for particular destinations in a medium sized German city. Supermarkets are chosen because they are frequently visited and a significant share of customers arrives by car. Supermarkets have also been identified as good destinations in recent literature (e.g.

Brooker and Qin (2015)). This makes the chosen segment of supermarkets a good fit to demonstrate our evaluation approach for destination charging.

4.5.1. Empirical data

We analyze the city center of a medium sized city in southern Germany. Starting at the city center, we identify 60 supermarkets with an ascending distance using the Google Maps API (Google Developers, 2018). We choose Google Popular Times as the base data source due to its wide area of application and destination specific information. Based on this set, we extract each destination's popular times which contains their degree of utilization for a week and the typical dwell time. As this information is not available for all identified supermarkets, we base our case study on the remaining 30 supermarkets. Google Popular Times uses hourly intervals to describe the utilization of a destination. Therefore, we first transform the utilization to one minute intervals. A detailed description of this step is given in Section 4.5.2. In a second step, we predict the arrival time of customers based on the typical dwell time and the utilization for each day, as already defined in Section 4.4.2.

4.5.2. Interval transformation

The simulation presented in this chapter is based on a time resolution of one minute. To integrate data sources with different resolutions, like for example the Google Popular Times with hourly resolution, an approach to transform the data is needed. There are two possible ways to do this: Extend the interval of the simulation to match the data resources or transform the data to the one minute interval. We choose the latter as hourly intervals would lead to unrealistic utilization profiles, where a large share of customer arrives and leaves the location at one point in time followed by no change for the next hour. In the context of destination charging, this might lead to an overestimation of the OL.

The approach presented here is based on the following assumptions: First, we assume a linear change in utilization between intervals. This is assumed as no additional information on the change of utilization within an interval is available. The utilization value is assumed to be the average and therefore, we allocate it to the center of the interval. Second, the transformation must consider the original opening hours of the location and not extend the total time of utilization. The transformation therefore has to ensure that the utilization is zero before and after the location is open. In this work, we show that the arrival time is an important factor for the profitability of destination charging and therefore an artificial extension of the utilization might lead to an underestimation of the OL.

We use the following approach to transform intervals of arbitrary length to a one minute interval. For a set of intervals I_a with $a \in 1, ..., n$ where n represents the total number of intervals, I_a represents a tuple with a start time t^a_{start}, a stop time t^a_{stop} and a utilization u^a. The center point of an interval a is referred to as c^a. An interval is considered a center interval if both the previous and the subsequent interval have a utilization greater zero. In this case, utilization is determined as follows:

$$u(t) = \begin{cases} \frac{1}{2} \cdot |u^a - u^{a-1}| + (t - t^a_{start}) \cdot \frac{u^a - u^{a-1}}{c^a - c^{a-1}} & \text{for } t \leq c^a \\ u^a + (t - c^a) \cdot \frac{u^{a+1} - u^a}{c^{a+1} - c^a} & \text{else} \end{cases} \tag{4.6}$$

For intervals following a utilization of zero, this is adapted to:

$$u(t) = \begin{cases} (t - t^a_{start}) \cdot \frac{u^a}{c^a} & \text{for } t \leq c^a \\ u^a + (t - c^a) \cdot \frac{u^{a+1} - u^a}{c^{a+1} - c^a} & \text{else} \end{cases} \tag{4.7}$$

Intervals followed by a utilization of zero can be calculated, respectively.

In Fig. 4.11, the extrapolation from a one hour interval (grey bars) to a one minute (blue line) resolution is shown. The figure also shows how due to the separate consideration of boarder intervals, the utilization stays within the original boarders and does not stretch due to the transformation.

4.5.3. Results

The scenario analyzed in the case study is similar to the one in Section 4.4. As supermarkets in Germany are closed on Sundays, the total number of EVs per week is reduced to 600. In addition, we move from self-generated usage patterns to the utilization provided by Google Popular Times. This allows for the integration of the destination's opening hours as well as a day specific utilization pattern. Google Popular Times provides the typical dwell time either as a constant or a range. In the former case, we use the constant as the typical dwell time of all agents. In

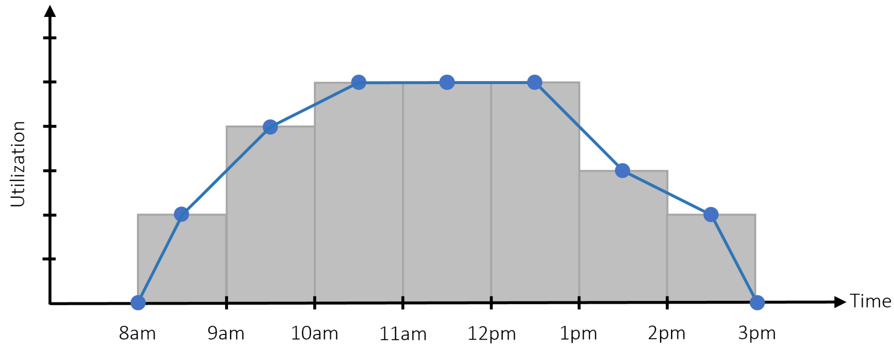

Figure 4.11.: Interval transformation

the latter case, the dwell time is uniformly distributed within the given time frame. We assume four charging points for each destination, 50kW charging power and a typical demand of 13.72kWh (see Section 4.4). The evaluation of all supermarkets is illustrated in Fig. 4.12.

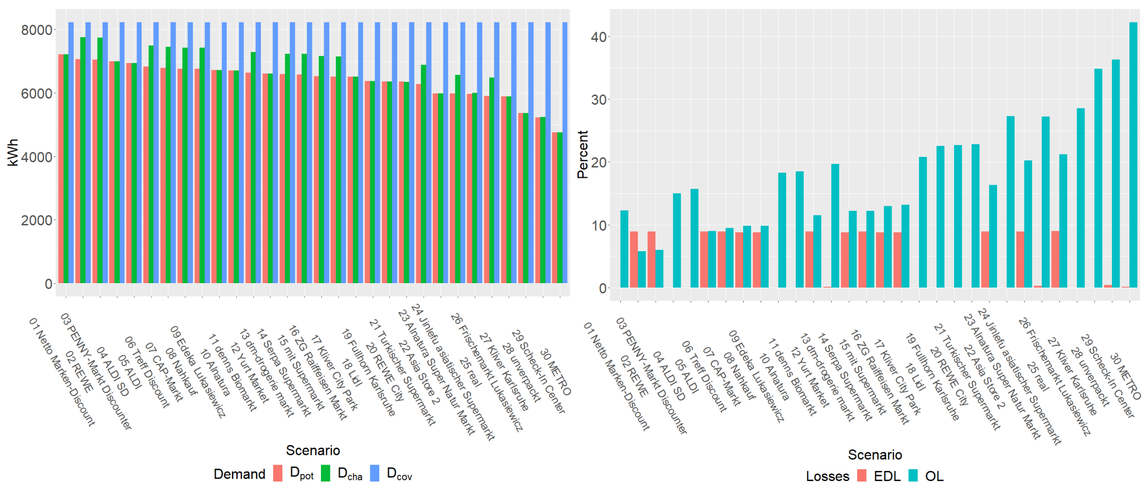

Figure 4.12.: Losses in demand due to user behavior for different supermarkets

The results show that destinations with a long dwell time exhibit bad results in the analyzed scenario. This can be explained by an increased OL. Customers at *Metro* have an average dwell time of 41 minutes, which is more than enough to charge 13,72kWh. Consequently, charging stations are blocked by fully charged EVs for a large share of the parking time. Hence, new customers cannot find an available charging station and park on a conventional parking spot. The results do not give an indication on an optimal dwell time. It is rather the combination with the other parameters that determine the profitability of a location. This can be demonstrated by comparing *Frischemarkt Lukasiewicz* and *Real*, two common supermarket chains in Germany. Both destinations' expected revenue is in the lower quarter of the evaluation but their average dwell time is rather different. With an average of 15 minutes, *Frischemarkt Lukasiewicz* belongs to the group of supermarkets with the shortest dwell time. As a consequence, 9% of potential demand is lost due to early departure. In comparison, the average dwell time at *Real* is almost twice as long with 29 minutes. This allows almost all customers to cover their demand completely and the EDL is negligible low with 0.3%.

The average dwell time can also be used to explain the OL of both destinations to some extent. At the destination *Real*, an average agent is only charging during 56% of the stay. After that, the agent unnecessarily blocks the charging station and prevents new customers from charging. This results in 27% of potential demand being lost due to occupancy of charging stations. In comparison, the destination *Frischemarkt Lukasiewicz* has a lower OL of 21% due to the shorter dwell time of customers.

The question remains why *Frischemarkt Lukasiewicz* has a rather high OL compared to other destinations with the same dwell time and why it performs almost equally bad as *Real* with a significantly longer dwell time. This can be explained by examining the utilization pattern of both destinations, which are illustrated in Fig. 4.13. *Frischemarkt Lukasiewicz* is characterized by a low utilization during the day with a strong peak in the afternoon. As a consequence, most of the charging stations are not in use during the day. When a large number of customers arrives in the afternoon, the charging infrastructure cannot meet the demand and many customers park on conventional parking spots. In contrast, *Real's* utilization is more evenly distributed for each day of the week. This allows the destination to utilize all charging stations throughout the day and to compensate for the long dwell time of customers.

Overall, the results highlight the importance of considering user behavior when evaluating locations for destination charging. Even though, all locations considered belong to the same segment, are open on the same days of the week and have the same D_{pot}, there is still a significant discrepancy in their predicted sold energy.

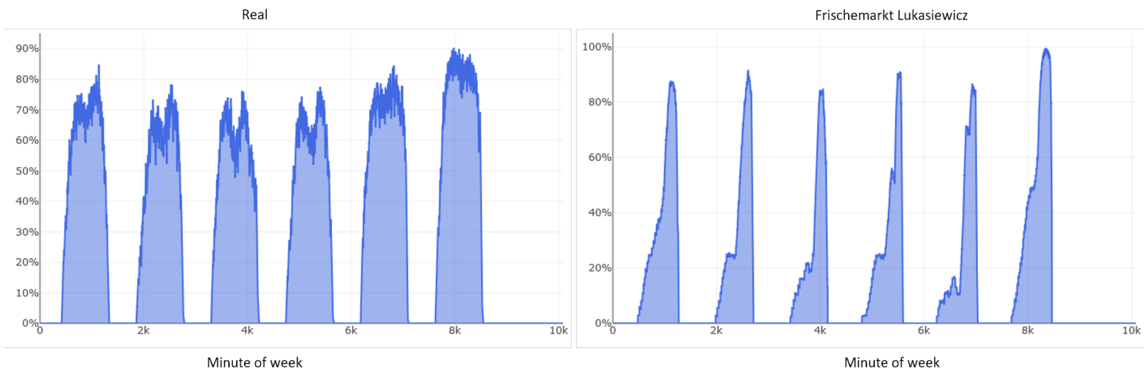

Figure 4.13.: Comparison Real - Frischemarkt Lukasiewicz

User behavior defines the arrival and dwell time of agents and influences D_{cha} in different ways. The case study further shows that there is no optimal dwell time for destination charging. It is rather the combination of all parameters that defines the potential revenue and therefore, the quality of a location for destination charging.

4.5.4. Limitations

The case study defines one exemplary scenario for external parameters in destination charging. This approach is adequate for the objective of this work, that is to highlight the importance of considering user behavior when evaluating potential locations for destination charging. As shown in Section 4.4, charging station operators have different options to counteract the losses associated with user behavior. Therefore, this case study does not cover all possibilities to evaluate supermarkets and different assumptions regarding charging speed or number of charging station may lead to other results. As increasing these parameters is linked to a higher investment, our approach can be used to determine the optimal trade-off between expected revenue and investment costs. In addition, the approach described in this chapter can be classified as an extension to current literature for determining D_{pot}. In real life, D_{pot} is not the same for all supermarkets as the absolute number of customers may vary.

4.6. Summary of Chapter 4 and Discussion

Destination charging describes charging sessions that are independent of the state of charge and where the activity at the destination is the primary objective of the customer. This leads to a new baseline in which the charging session follows the boundaries of the driver's stay. From the perspective of a charging station operator, this influences the usage of the charging station and therefore, the economic evaluation of charging stations. Current literature evaluating the location of charging stations does not account for user behavior at the particular destinations, hence, the expected revenue might be overestimated. The contribution of this chapter is threefold:

1. We show that considering user behavior is essential in the context of destination charging. This is done by defining the Early Departure Loss and Occupancy Loss, both associated with user behavior. We also formulate the change of potential revenue for charging station operators.

2. We analyze various scenarios to quantify the losses and to gain knowledge on the influence of user behavior. In addition, we provide insights on how to counteract the losses by adjusting the infrastructure provided.

3. We apply the findings to a real world use case and demonstrate that even within one domain, user behavior and therefore, expected revenue varies between locations, highlighting the importance of considering user behavior in the context of destination charging.

In conclusion, the contributions show that in regards to Research Question 2, the parking patterns do have an impact on the success of public destination charging. This impact can be quantified using the Occupancy Loss as well as the Early Departure Loss, which can reduce the covered demand of locations by more than 40% in a real world setup.

The main assumption of this chapter is that EV owners are not willing to change their behavior in order to charge their vehicle. Charging at destinations is convenient, as EV owners can do what they like during the charging period (Luo et al., 2018). Further research should focus on how and to what extent EV owners are willing to adapt their stay in order to improve their charging experience. A potential instrument to do this might be pricing, e.g. with a specific charging tariff design or benefits at the location, like discounts. Together with these insights, there is the possibility to improve the revenue at destinations that suffer from losses with today's user behavior. Furthermore, we assume that the dwell time of agents is the same at all times. Further research should focus on potential variance in dwell time and include this data into the simulation. In addition, further and more detailed data is needed to evaluate the exact user behavior at a location.

From the perspective of a CPO, the results of this chapter show that using potential demand at a location is not sufficient for destination charging as further losses have to be expected. Both, the availability of charging stations and the dwell time of EV owners reduce the revenue and therefore need to be considered. From the EV users' perspective, however, the results demonstrate that there are multiple locations that allow charging the vehicle successfully while parking. In such a scenario, public charging can help users to cover their demand while following their established mobility pattern.

In conclusion, Part II provides insights on the impact of user behavior on both, private and public charging and consequently supports academics to consider user behavior when coordination charging behavior of private EV users. Further, the results provide management insights, especially for CPOs, on how to include user behavior into the economic evaluation of charging locations, which helps to reduce the financial risk of the investment into charging infrastructure. This section is based on particular empirical data of individual users. However, private EV owners do not represent the entirety of potential customers. Based on vehicle registrations, commercial users also provide the opportunity for EVs to enter the mainstream market and therefore, should be analyzed in more detail. This is done in the following section, where novel approaches to identify promising charging strategies that consider the unique challenges of commercial fleets are introduced and evaluated.

Part III.

Charging Commercial Electric Vehicles

Introduction to Part III

The third part of this dissertation shifts the focus from private EV users towards commercial fleets. Similar to the possibilities of private EV owners, commercial fleets have the opportunity to either establish charging infrastructure at their company's depot or rely on public charging stations. While in the case of private EV users the person investing in a private charging station and the user of the vehicle typically are the same person, this does not apply to a commercial fleets. Here, a fleet manager has the possibility to build charging infrastructure as well as coordinate the charging sessions, whereas the users that drive the EV have to act within the provided framework. This is addressed in Chapter 5 where a decision support tool for fleet managers is introduced which allows for the identification of fleets with a high potential for electrification. Furthermore, the decision support tools helps to determine a promising charging strategy for commercial fleets. The findings of the tool help to foster EV adoption as it provides the identified fleets to switch from ICEVs to EVs while being able to provide the needed infrastructure themselves, as they do not rely on a third party. However, the results also show that not every fleet can rely solely on private charging stations. Therefore, Chapter 6 extends the scope to public charging stations. Using empirical data from taxi trips in the city of Chicago, a set of charging strategies are developed and evaluated using an agent based simulation. The analysis quantifies the possibilities of taxis to improve their operational return using off-peak charging or the CPO's potential to support taxis with additional charging stations at frequently visited locations. In conclusion, this part introduces systems for commercial EV users to coordinate their charging behavior to maximize their share of successful electrically driven trips as well as their operational return.

Chapter 5.

Decision Support for Charging Electric Fleets

Commercial fleets account for around two thirds of new car registrations and thus represent a compelling customer group for EVs (KBA, 2021). Consequently, the third quadrant of the matrix shown in Figure 1.1 explores the potential of commercial fleets to adopt EVs while covering their demand using charging infrastructure at their premise. Even though there is evidence that the mobility patterns of fleets are more predictable (Detzler, 2016), the way they are operated can vary substantially. To consider these dissimilarities, this chapter analyses the mobility patterns of 81 fleets using an agent based simulatiFeron. Based on the findings of this simulation, a decision support system is developed that allows fleet managers to identify fleets with great potential for electrification using a simple First-Come-First-Served charging strategy. These findings provide management insights that help to prioritize fleets with a mobility pattern that allows a successful electrification today. For the remaining fleets, the results of the simulation provide recommendations on how fleet managers can improve the share of successful electric trips by adapting their charging strategies, using both foresight and automation. This chapter comprises the results of Schmidt et al. (2021) published in *Transportation Research Part D: Transportation and Environment* and is a joint work together with Philipp Staudt and Christof Weinhardt.

5.1. Introduction to Fleet Electrification

There are several studies that focus on the impact of electrification from an environmental (e.g. (Donateo et al., 2015; Spangher et al., 2019; Škugor and Deur, 2015)), economical (e.g. (Hsieh et al., 2020; Schücking et al., 2017; Tomić and Kempton, 2007; Haller et al., 2007)) or technical (e.g. (Bischoff et al., 2019; Tu et al., 2019; Morganti and Browne, 2018; de Gennaro et al., 2014)) perspective. Especially research focusing on the technical limitations of EVs mainly investigates if one particular fleet can be electrified and what charging strategy is most likely to perform well given the fleet's mobility pattern. Based on this research, the question remains if the results can be generalized and applied for different commercial fleets with the aim of identifying new fleets that are good candidates for electrification. In the current literature, there is a lack of research focusing on a general decision support system (DSS) to provide guidance to fleet managers on whether and how their fleet can be electrified. With our study, we want to address this research gap and provide further insight on the impact of a fleet's mobility pattern and charging strategy on the potential for electrification and identify fleet characteristics that indicate a high potential for electrification for commercial fleets in general and given particular charging mechanisms.

Therefore, in this chapter, we focus on a technical analysis of fleet electrification starting with the mobility patterns of different fleets. Focusing on the current state of charging infrastructure, we assess a scenario where a fleet vehicle is only charged at the company depot and therefore not reliant on public charging infrastructure. In this setup, the fleet manager has the ability to provide the necessary charging stations, which reduces the risk of blocked or non-existing charging infrastructure. We acknowledge that charging at public charging stations is a viable option for many fleet vehicles. Nevertheless, searching for charging stations introduces an additional level of uncertainty and opportunity costs and hence a risk to a fleet's economic operation, which might hinder EV adoption. Identifying commercial fleets that can adopt EVs without any change in their mobility pattern while only charging at the company base, represents an easier and faster to implement scenario and should therefore be researched in more detail.

Research Question 3 of this dissertation assesses today's fleet mobility patterns and under which circumstances electrification is possible without any changes in behavior with given limitations of the vehicle and charging infrastructure. For a more detailed understanding, Research Question 3 is divided into three sub-questions. Based on the the mobility patterns of a broad range of fleets, we first determine naive benchmarks to set the technical limits of electrification that we later try to achieve using heuristics, automation and different levels of operational foresight.

RQ 3.1 To what degree are commercial fleets suited for electrification considering the technical limitations of the vehicles and charging infrastructure?

The findings of Question 3.1 are based on complete information over future trips of a fleet and therefore represent an upper bound for the potential of electrification for a single fleet. The results provide insights on which fleets' mobility patterns are a good fit for electrification and they can also be used as a benchmark for different charging approaches. To account for the limited information during a real world operation of fleets, we extend our analysis to determine charging schedules using heuristics that we apply in a simulation on the data of 81 real word vehicle fleets and benchmark the results against the case with complete information. Using the fleet mobility patterns, we then identify characteristics that indicate a high potential for a heuristic charging mechanism leading to an extension of the research question where an optimal charging schedule is a charging schedule optimized given complete information:

RQ 3.2 Which fleet characteristics indicate a fleet's potential to achieve a close to optimal charging schedule using heuristics?

The mobility pattern of every fleet is different and hence, not every fleet can operate up to its potential using a heuristic approach. To address this, we analyze two measures to improve the charging approaches. On the one hand, we add the possibility to automatically allocate and reallocate vehicles to charging stations. This allows for a more efficient usage of existing charging stations and eliminates fully charged EVs blocking charging points for others. We call this measure *automation* as opposed to manual charging. On the other hand, we bridge the gap between heuristics with no information on future trips and the scenario with complete information by a stepwise increase in foresight and an according optimization given the available knowledge. We call this measure *optimization* as opposed to rule based charging. This information is especially important for fleet managers that seek ways to increase their electrification efforts leading to the second extension of the research question:

RQ 3.3 Which fleet characteristics indicate a benefit from an automated charging allocation or an increase in forecasting ability of future trips?

All research questions are complemented with a decision tree that allows a fleet manager to classify whether their fleet can profit from certain charging strategies and what benefits might be expected. The main contribution of this chapter is therefore the possibility to characterize commercial vehicle fleets in regards to the possibility of their electrification using different charging mechanisms that require different levels of operational foresight and automation. For academic readers, this deepens the understanding of the impact of behavior in regards to the electrification of the transportation sector. For practitioners, the results can be used to identify mobility fleets that have the potential to be electrified and provide decision support for further improvement.

5.2. Related Work

There are several studies focusing on the electrification of vehicles with different objectives. One question broadly discussed is if and under what circumstances vehicle owners adopt EVs (Bjerkan et al., 2016; Rezvani et al., 2015). In the private sector, convenience and a fit to the drivers mobility pattern has shown to be a good approximation for EV adoption. Tamor et al. (2013) show that people do not switch to EVs if a certain share of trips cannot be fulfilled. As a metric, they use the frequency of trips where an alternative mode of transportation is needed. He et al. (2016) follows a similar approach by determining the number of days that the EV range exceeds the trip length and alternative transportation is needed. They show that with a range of 150km and a threshold of 52 days, 86% of drivers would switch to an EV.

The commercial sector differs from the private sector in the regard that the person buying and the person driving the EV are not necessarily the same. Kaplan et al.

(2016) propose a framework that focuses on understanding the motivation of firms to include EVs into their fleets and particularly the characteristics of the fleet manager. The authors of (Globisch et al., 2018) study the motives of car pool managers to campaign for EV procurement within their firm and find that personal interest in EVs due to technophilia has a strong positive impact. With our study, we want increase the ease of switching to an electrical fleet through the analysis of fleet mobility patterns and according charging strategies.

In fleets that already use some EVs, experience is a key factor. Ehrler and Hebes (2012) show that in city logistics, the attitude towards the technology increases with practical experience. Wikström et al. (2014) also show an increase in EV usage with gained experience.

Another focus in current literature is the economical analysis of a transition towards EVs. Hsieh et al. (2020) examine the cost competitiveness of business models connected to charging EVs for double-shift taxis in Beijing. Their results show that battery swapping is a cost-effective option on a per-kilometer basis. In the work of (Haller et al., 2007), the conversion of a fleet used by a local government is examined with the focus on cost effectiveness and environmental impact. Besides the conversion cost, the infrastructure investments required are calculated. In Raab et al. (2019), the authors define a charging schedule for an electric bus fleet. Based on the travel schedule of individual vehicles, the charging strategies are negotiated in advance, ignoring any uncertainty during operation. In addition, electric fleets allow companies to earn money while the vehicles are stationary. Tomić and Kempton (2007) show that two utility-owned fleets of EVs can generate significant potential revenue streams using V2G. Based on the same technology, Staudt et al. (2018) aggregate EVs into an virtual fleet to reduce redispatch in Germany and calculate the potential revenue per vehicle based on their location.

Besides the economical research, other authors focus on the technical possibilities of an EV adoption. Tu et al. (2019) analyze ride hailing trips in Beijing based on GPS data. Their results suggest that depending on the infrastructure, 47% to 91% of drivers could switch their ICEV to an EV if the EV battery range was more than 200km. (Gnann et al., 2015) calculate the market potential of commercial EVs and find that 87% of driving profiles can be technically fulfilled with an EV with 110km of battery range. The authors of (de Gennaro et al., 2014) use the mobility pattern of private and commercial light duty vehicles in the Italian provinces Modena and Firenze to explore the potential for electrification. Their results show that without any change in travel patterns, between 8% and 28% of vehicles can be electrified. In the work of de Almeida Correia and Gonçalves Santos (2014), a model to optimize the trip assignment of EVs and ICEVs in a regional rental company in Portugal is introduced. Nevertheless, a common limitation of literature focusing on providing adequate charging infrastructure for EVs and hence providing insights on the technical feasibility of fleet electrification is the missing consideration of actual driving patterns or the restricted view on a specific city or metropolitan area (Gnann et al., 2018). We intend to fill this research gap with our study.

Despite research showing how EVs can economically be integrated into selected fleets and the resulting positive impact on the environment and the technical research showing that there are scenarios where EVs are a viable option today, the question remains if the results can be generalized to a wide range of fleets.

There is literature with a broader view on electrification, as, for example, Betz et al. (2016), who analyze a mixed fleet of EVs and ICEVs with the goal of distributing trips among the vehicles while coordinating EV charging. The results provide a customized recommendation for the optimal fleet composition. While the simulation is used to calculate the impact of adopting fast charging infrastructure, there are no insights given to how different mobility patterns influence the result leaving room for a generalized DSS.

The concept of using DSS to address questions regarding electric mobility is not new and has been applied in several studies. (Barfod et al., 2016) provide a DSS for analysing the process of EV adoption based on challenges, opportunities and policy incentives. The authors of (Beverungen et al., 2015) and (Kloör et al., 2018) focus on the second life of EV batteries and develop a DSS that supports decision concerning the reuse of disused batteries. In (Bersani et al., 2019), the optimal location of charging infrastructure is determined using a DSS.

However, to the best of our knowledge, there is no work using the strength of DSS and the knowledge of the technical possibility for fleet electrification to analyze the potential of a broad range of commercial fleets for electrification using mobility patterns. In addition, there is a need for guidance to counter potential challenges when adapting EVs in a fleet. In this chapter, we address this gap by defining benchmarks to evaluate the potential for electrification, providing a quantitative simulation of different mobility patterns and evaluating the possibilities to counter potential restrictions and limitations using heuristics, automated relocation at charging stations and limited foresight to adapt the EV charging strategies.

5.3. Method

In this section, we introduce the characteristics used to describe a fleet's mobility pattern from which we later derive the electrification options for the fleet. In addition, we present the framework that we employ to assess the fit of a commercial fleet for electrification, the data and parameters used as well as the simulation setup.

5.3.1. Fleet Mobility Pattern

The mobility pattern of fleets varies widely depending on the sector of the fleet, the area of operation or the customers served by the fleet. Some fleets, as, for example, the ones used in last-mile-delivery, have a small radius and a predefined time of operation whereas other fleets, like taxis, have no geographical limitations and uncertain operation schedules. As a consequence, there is a need for characteristics that describe a mobility pattern to allow a comparison between fleets. In this section, we partly base these characteristics on (Kaplan et al., 2016), who use the average number of depot based daily tours, the average daily tour duration, the average number of pick-ups, drop-offs and rest stops per tour, the share of a vehicle fleet that has a tour length of under 50km to 400km in increments of 50km and the share of vehicles that have at least one 30 minutes stop. Based on these 5 characteristics, Kaplan et al. (2016) are able to represent a fleet's operational usage.

Whereas the basic idea of the characteristics can be applied to the setup of this work, we adjust them slightly to better incorporate the research objective and the used data set. At first, as we only analyse depot based trips and do not allow any charging sessions between the legs, we neglect the number of pick-ups and drop-offs per tour. In addition, we reduce the differentiation of fleet tour lengths in steps of 50km to the average trip length. This is done to increase the interpretability and to allow for an easier comparison between fleets. Finally, we change the share of vehicles with a break of at least 30 minutes to the average break time between trips. This is necessary as the data used covered an average of around 3 weeks of documented trips in which almost every vehicle had a break longer than 30 minutes (compare Section 5.3.5). As a consequence, the characteristic does not provide any valuable information to compare commercial fleets. The average break time on the other hand can be used as an indication to the extent of a vehicle's availability at the company depot for charging.

5.3.2. Framework

Besides the characteristics of a fleet's mobility pattern, both, a performance measure to quantify the degree of electrification of every fleet and a framework to set theses values into perspective are needed in order to answer the research questions. Following the research of (Tamor et al., 2013), we focus on the number of successful trips after electrification and define the share of successful trips as our key performance indicator (KPI). A trip of a commercial vehicle is successful if the state of charge (SoC) at the beginning of a trip is sufficient to reach every stop along the tour and to complete the trip back to the fleet base without the need for recharging. Trips that do not fulfill this criterion cannot be performed and are canceled before departure.

We thus define the share of successful trips α of a company fleet i with a total number of n_i trips as

$$\alpha_i = \frac{\sum_{v \in V_i, t \in T} s_{v,t}}{n_i} \tag{5.1a}$$

where

$$s_{v,t} = \begin{cases} 1, & \text{if } trip \text{ is successful} \\ 0, & else \end{cases} \tag{5.2a}$$

describes if a trip of a vehicle $v \in V_i$ starting at $t \in T$ was successful. V_i describes the set of all vehicles of fleet i. Consequently, the objective of heuristics developed and evaluated in this section is to enable EVs to execute every trip done by ICEVs and to achieve an α_i of 1. This benchmark is defined as α_{total}.

Nevertheless, EVs have certain technical limitations, such as their lower driving range that can make an α_i of 1 impossible. As our fundamental assumption is that vehicles are only charged at the fleet base, trips that exceed the battery range of the EV become technically infeasible and hence cannot be performed regardless of the charging infrastructure and smart charging strategy. In this context, smart charging refers to any charging strategy intended to improve the fleet's α_i by modifying the charging schedule. To comply with this technical limitation, we define a second benchmark called $\alpha_{tech,i}$. This benchmark represents all trips that are technically feasible with an EV with predetermined specifications, while assuming an SoC of 100% at the beginning of every trip and ignoring charging time.

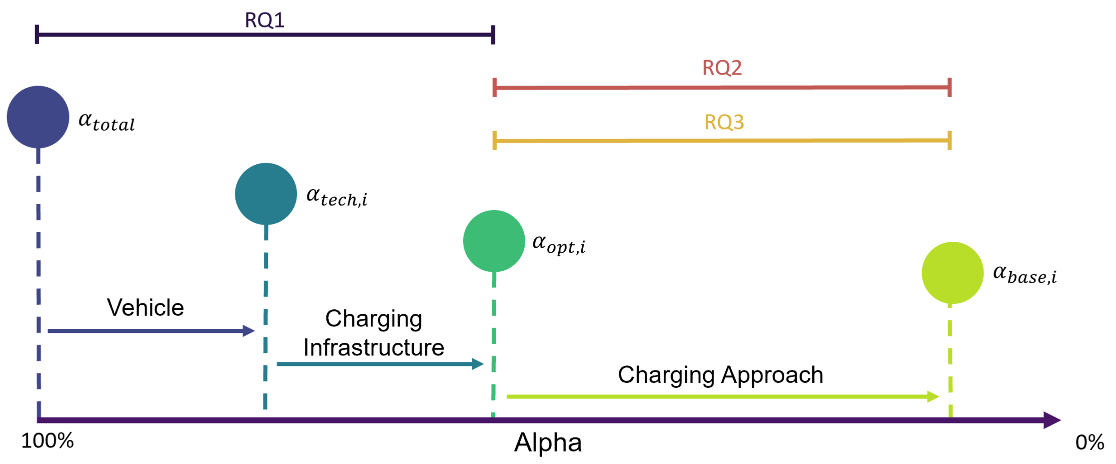

Figure 5.1.: Limitations of fleet electrification and benchmarks

The second technical limitation is the available charging infrastructure and required charging time. Depending on the available grid capacity and number of charging stations, the power distributed to EVs is limited. To account for limitations given by the infrastructure, we define $\alpha_{opt,i}$. For this benchmark, the optimized charging algorithm has complete information on future trips and schedules charging sessions, correspondingly. The allocation of EVs to a charging station is assumed to be automated. *Automated* in the context of this work refers to a mechanism where EVs can be assigned to charging stations and receive power according to the sites technical limitations without any time delay and without requiring intervention, for example by providing sufficient charging points for all vehicles, which can be switched on and off while respecting a given grid capacity restriction. Hence, $\alpha_{opt,i}$ represents the upper bound of successful trips for a predetermined charging infrastructure and predetermined EV specifications at the fleet base.

Besides the upper technical limitations of EV adoption, we also define a benchmark representing the transition to EVs without implementing any optimization. For this benchmark, there is no automated allocation and EVs are assigned to charging stations based on a simple First-Come-First-Served heuristic. This benchmark is referred to as $\alpha_{base,i}$. We acknowledge that this benchmark does not necessarily represent the absolute worst performance of a fleet electrification, but rather an electrification without modifications to support the transition, which can be understood as a naive benchmark.

Given the four benchmarks $\alpha_{total}, \alpha_{tech,i}, \alpha_{opt,i}$ and $\alpha_{base,i}$, Research Question 3.1 analyzes the difference between $\alpha_{base,i}$ and α_{total} for different mobility patterns. In a second step, we investigate how different smart charging strategies based on foresight and technical modifications of both the infrastructure and automation can help to improve the number of successful trips for different fleet mobility patterns and we compare them against $\alpha_{opt,i}$ and $\alpha_{base,i}$.

5.3.3. Optimization Problem

The benchmark $\alpha_{opt,i}$ describes the maximum of viable trips if EV specifications, charging infrastructure and technical limitations while charging are considered and all needed trips are known in advance. To determine the benchmark for a given fleet mobility pattern, we specify a linear optimization problem to allocate EVs to charging stations. The objective of the problem is to maximize the number of successful trips of a fleet i as the sum of $s_{v,t}$ for every vehicle $v \in V_i$ for every time interval $t \in T$.

With Constraint 5.3b, we ensure that a vehicle can only be assigned to a charging station $a_{v,t}$ if it is at the fleet base. In addition, the number of vehicles charging simultaneously must not exceed the number of charging stations CP provided at the fleet base (Constraint 5.3c). In Constraint 5.3d, we define that a successful trip $s_{v,t}$ is only possible if the vehicle v is scheduled to depart within time interval t, represented

$$
\begin{aligned}
&\max \sum_{v \in V_i, t \in T} s_{v,t} && && (5.3a)\\
&\text{subject to} && &&\\
&a_{v,t} \leq 1 - s_{v,t_d} && \forall v \in V_i, t \in T && (5.3b)\\
&\sum_{v \in V_i, t \in T} a_{v,t} \leq CP && && (5.3c)\\
&s_{v,t} \leq \lceil l_{v,t} \rceil && \forall v \in V_i, t \in T && (5.3d)\\
&SOC_{v,0} = SOC_v^{Initial} && \forall v \in V_i && (5.3e)\\
&SOC_{v,t} = SOC_{v,t-1} + a_{v,t} * p_{v,t} - s_{v,t} * l_{v,t} * c_v && \forall v \in V_i, t \in T && (5.3f)\\
&a_{v,t}, s_{v,t} \in \{0, 1\} && \forall v \in V_i, t \in T && (5.3g)\\
&0 \leq p_{v,t} \leq p^{max} && \forall v \in V_i, t \in T && (5.3h)
\end{aligned}
$$

by a desired trip length $l_{v,t} > 0$. The desired trip length is retrieved from the data set of the recorded trips. Constraint 5.3e and 5.3f focus on the SoC of the EVs, where the former defines the initial SoC at the beginning of the optimization problem and the latter the change of SoC due to charging or a successful trip.

To solve the mixed integer program, we use the Gurobi Solver. By solving this optimization problem, we are able to define an optimal charging schedule for every fleet and therefore, are able to determine the upper bound of successful trips $\alpha_{opt,i}$ for every fleet i.

5.3.4. Scenarios

Given that the optimal schedule is determined, we now move to the operation of EV fleets under uncertainty. In this section, we describe the different smart charging scenarios employed in this chapter. In a first step, the different approaches to allocate EVs to charging stations are explained.

Heuristics

Heuristics represent simple rule based approaches to allocate EVs to charging stations and are used to get a first impression of the electrification of fleets but also represent a class of charging strategies that can be used without sophisticated computational infrastructure.

First-Come-First-Served The scenario S_{base} with the resulting lower bounds $\alpha_{base,i}$ follows a simple First-Come-First-Served approach. In this charging strategy, an arriving vehicles checks if there is a charging station available. If this is the case, the vehicle is allocated to the charging station and the status is set to charging. Otherwise, it will be parked at a regular parking space. Vehicles will not be removed from charging stations once the battery is completely charged and will only unplug at the departure for the next trip. Vehicles that are not parked at a charging location will not be charged before their next trip.

Lowest-SoC-First (M) Another simple strategy is to charge the vehicle with the lowest SoC. In the manual heuristic (M), allocating vehicles to charging stations is only possible, if a vehicle arrives at or departs from the company base. The driver then selects the vehicles with the lowest SoC and connects them to the charging station. The vehicles remain at the charging stations until the next vehicle arrives and a new allocation is calculated.

Lowest-SoC-First (A) In the automated form of this heuristic, the situation is reevaluated at every time step. Hence, charging stations will only be blocked if all other vehicles are fully charged.

Random (M) This heuristic follows the same procedure as the Lowest-SoC-First heuristic (M), but rather than choosing the vehicles according to their SoC, random vehicles (including those that are fully charged) are allocated to the charging stations. In this heuristic, every vehicle that is either parked or charging at the fleet base has the same chance to be selected for charging in the next time period regardless of the current SoC.

Random (A) In this extension of the Random heuristic, the allocation mechanism is automated and can therefore be performed anew at every time step.

We acknowledge that the described heuristics do not represent the full spectrum of simple approaches to allocate EVs to charging stations and many more can be integrated. Nevertheless, they cover a case where no explicit rules are specified (First-Come-First-Served), a case that takes the vehicles' SoC into account (lowest-SoC-first) and a completely randomized case as a benchmark. This provides a good foundation for answering our posed research questions.

In addition to S_{base}, we evaluate all 4 scenarios based on heuristics labeled as S_x^y and the resulting $\alpha_{x,i}^y$ for every fleet i where $x \in [LSOCF, random]$ represents the name of the heuristic and $y \in [M, A]$ whether a manual or automated allocation is used.

Foresight

Besides heuristics, we also analyze the impact of the availability of information on future trips. For different fleets, the knowledge on future trips varies. Whereas some follow a schedule and can hence tell the departure time and distance ahead of time, others do not have this benefit. In this regard, our objective is to evaluate if fleet operators should invest time and effort into improving forecasts of their vehicle usage patterns or if there are other less costly alternatives, namely heuristics, that do not lead to a large difference in the share of completed trips.

We define foresight as the planning horizon within which complete information on trips is available. This means that within the foresight period, the fleet operator has no uncertainty and can schedule the charging sessions, correspondingly. Outside the foresight period, no information is available and we assume that no prediction of trips is possible.

To calculate the optimal charging schedule within the foresight period, we use a modified version of the optimization problem described in Section 5.3.3. First, the objective function is modified to reward a high SoC of vehicles. This is necessary, as the end of the optimization does not represent the end of the simulation. Therefore, even if all trips within the foresight can be completed successfully, the charging stations should not remain idle. By using the Big-M method, we ensure that the optimization problem always charges vehicles if possible without affecting the feasibility of completing anticipated trips.

$$\max \sum s_{v,t} + \sum_{v,t} SOC_{v,t}/M \tag{5.4a}$$

Besides the objective function, we define the SoC at $t = 0$ as the current SoC of the vehicle and limit the range of t to $[0, f]$, where f represents the time intervals of foresight.

In total, we analyze three scenarios with varying foresight periods. For a fleet i, the scenario S_f and the resulting $\alpha_{f,i}$ is characterized by a foresight period of $f \in [foresight60, foresight360, foresight1440]$ which represent a foresight period of 1, 6 and 24 hours. An overview over all scenarios analyzed in this study and their main differentiation is given in Figure 5.2.

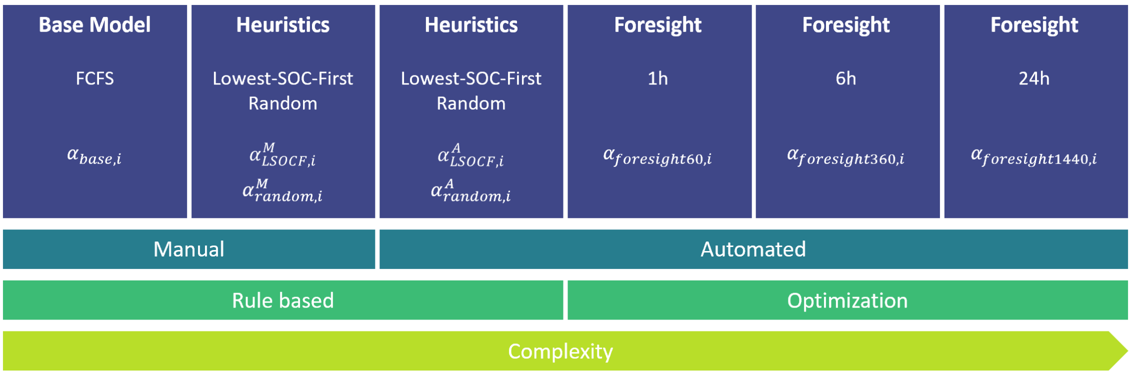

Figure 5.2.: Overview and characterization of charging scenarios

5.3.5. Input Data

REM2030 The quantitative analysis of this work is based on the REM2030 database (REM 2030, 2020). The database contains 630 driving profiles from commercially licensed vehicles in Germany, with information on the departure and arrival time, the distance traveled and the vehicle size. Besides information on the vehicle and its mobility pattern, the database also contains information on the associated company, like its size and economic sector (NACE Section). In total, the mobility patterns of 178 fleets are recorded with a fleet size of 1 to 14 vehicles and an average of 3.53 vehicles per fleet. For our investigation, we focus on fleets with 3 or more vehicles.

The REM2030 database does not contain the exact location of vehicles but rather the distance to the fleet base for every stop. We assume a vehicle to be positioned at the fleet base, if the distance to the fleet base is equal or below 100 meters. Every stop within this radius is considered to be at the base and hence the vehicles can be charged. In addition, we aggregate all consecutive trips outside the fleet base such that every documented trip starts and ends at the fleet base. Vehicles that never visit the fleet base are excluded from the database. In total 81 fleets remain and are analyzed.

Within the database, the variance of the distance traveled by the fleets is high. With an average of 6,160 traveled kilometers documented per fleet and a range between 699km and 64,960km (SD 8,279km), the energy demand also differs largely between fleets. As a consequence, assigning the same aggregated charging power (grid capacity) to every fleet base benefits fleets with a lower distance traveled or fewer documented trips and therefore influences the potential for electrification. While we acknowledge that fleets with lower distance traveled have an advantage in regards to electrification, the focus of this chapter is to analyse the impact of the full set of characteristics of the mobility patterns. To account for the variance in distance traveled, we use a different approach to determine the grid capacity for every fleet which is explained in the following paragraph.

Grid Capacity The available grid capacity has a strong impact on how fast and how many vehicles can be charged at the same time. To allow a comparison between different fleets, we normalize the assigned grid capacity to the actual demand of a fleet. We do this by defining the theoretical grid capacity $c_{avg,i}$ needed by fleet i to allow a full electrification of the fleet to cover all trips within the REM2030 database, while assuming the continuous availability of EVs at the company site.

$$c_{avg,i} = \frac{\sum trips_i * consumption}{recordedtime} \tag{5.5a}$$

The value c_{avg_i} is a theoretical lower bound for the grid capacity needed to allow a successful continuous operation of the fleet and therefore represents minimum grid capacity needed for a successful electrification. Hence, c_{avg_i} puts every fleet in the same position where grid capacity is scarce and the charging schedule should continuously charge vehicles. The advantage of this approach is that it allows for a better comparison of the impact of different charging strategies and automation on the electrification of commercial fleets and thus puts a stronger focus onto our research questions. In addition, it represents a lower bound for the infrastructure, which helps with the goal of identifying fleets that are a good candidate for electrification.

Infrastructure and EV specification The specifications of the fleet base and vehicles are chosen to represent the currently available technology. We differentiate between parameters connected to the charging infrastructure and the EVs. The infrastructure at the fleet base is set to two charging stations, each with a maximum output of 11kW. 11kW represents charging with three phases at 32A and is standard in many vehicles available today (e.g. Tesla Model 3 (Tesla, 2020), VW ID.3 (Volkswagen UK, 2020)). However, the aggregated charging power of both charging stations must not exceed the grid capacity of a fleet.

The EV battery capacity is set to 40kWh (Hyundai, 2020; Nissan, 2020) with a consumption of 0.2kWh/km (Liu, 2012; Seddig et al., 2017), resulting in a range of 200km. The specifications of the EVs are chosen to represent an average vehicle currently available. At the beginning of a simulation, the SoC of every vehicle is set to 80% in both the optimization and heuristic approaches. An overview of the selected parameters is given in Table 5.1.

Table 5.1.: Overview Parameters

Infrastructure Parameters		Vehicle Parameters	
Number of Charging Stations	2	Initial SoC	80%
Power Charging Station	11kW	Battery Capacity	40kWh
Grid Capacity	c_{avg}	Consumption	0.2kWh/100km

The input data and specifications defined in this section are the basic assumptions for the analysis and, unless explicitly specified, are identical for all simulation runs. On the basis of these specifications, different scenarios are described in the next section.

5.3.6. Simulation

For the quantitative evaluation of our work, we implement a python based simulation. Starting with the REM2030 database, we first aggregate all individually documented legs of a trip into a single trip where multiple stops outside the fleet base are documented (compare Section 5.3.5). After this step, every trip of every vehicle starts and ends at the fleet base.

The central part of the simulation is calculated for every fleet consecutively. In the first step, the parameters of the scenarios are defined as described in Table 5.1. Then, the following methods are called.

getNextEvent To decrease the calculation time, the simulation does not iterate through every time step of the observation period but rather iterates through events where choices have to be made. These events depend on the charging strategy and the assumptions made. In scenarios, where reallocation of EVs is done manually, the only events are the arrival and departure of an EV. In all other time intervals, the heuristic cannot influence the status of vehicles. In the automated case, this changes as EVs can be redistributed all the time. Hence, the next event is the next time interval. For scenarios using the forecast based optimization, the next event is at the end of the previous foresight period. This is necessary due to runtime constraints but does not affect the results considerably due to the long forecasting horizons.

VehicleDeparture Every vehicle of a fleet can either be in the status *parking*, *driving* or *charging*. At $t = 0$, all vehicles are parked at the fleet base. For every event, the simulation checks all scheduled trips for the time period. A vehicle status is set to *driving* if a trip is scheduled and the SoC is sufficient to complete the full trip. Otherwise, the vehicles remains in its initial state.

AssignChargingSchedule In the next step, the simulation determines the charging schedule. A complete description of the strategies is given in Section 5.3.4. The strategies differ in the set of vehicles considered for charging. Whereas manual heuristics only allow arriving vehicles to be assigned to *parking* or *charging*, automated heuristics are also capable of assigning *parking* EVs to charging stations and vice versa.

Charge After the charging schedule is calculated, the new status is assigned to the vehicles. In the last step, all vehicles allocated to a charging station are charged according to grid capacity and charging station limitations. These steps are repeated for the whole observation period. A detailed description of the simulation is given in Algorithm 2.

Algorithm 2: Fleet Electrification Simulation

```
Data: REM2030 2015
aggregateTrips();
Main: Main
t = 0;
while t ≤ T do
    VehicleDeparture();
    AssignChargingSchedule();
    Charge();
    t = getNextEvent()
```

5.4. Results

In the following, we present the results of the quantitative analysis including the simulation. Besides the benchmarks and the charging strategy results, we also present a classification using the fleet characteristics that shows which fleets should use which strategy and how much effort operators should invest into improving a forecasting ability. This is meant to support researchers in deciding for which cases smart charging strategies need to be further developed and to help practitioners to locate their fleet within the spectrum of possible charging strategies.

5.4.1. Impact of technical limitations of EVs

In this section, we focus on the question whether the technical limitations hinder or even prohibit the adoption of EVs in various fleets and evaluate the described benchmarks.

Limitations of the vehicle The technical limitations connected to the vehicle are mapped to the benchmark $\alpha_{tech,i}$. By looking at the battery range of the EVs and the planned trips, we can verify that the concept of only charging at the fleets' bases is a viable option for the fleets analyzed in this work. The average α_{tech}^{avg} over all 81 fleets is 91% in the REM data set and is therefore a strong indication that the parameters chosen for our simulation are sufficient for an electrification of most fleets. Within different sectors, there are different $\alpha_{tech,i}$ values with a range of 80% to 99%. On overview over all sectors is given in Table 5.2.

Overall, half of the fleets analyzed have an $\alpha_{tech,i}$ greater than 95% (25%-Quantile = 86%, 75%-Quantile = 100%) and therefore allow almost the same mobility using EVs as with ICEVs. In Figure 5.3 (left), a histogram of all $\alpha_{tech,i}$ values is given. Nevertheless, there are still two fleets with a particularly low $\alpha_{tech,i}$. With an alpha of 20%, fleet 120205 has the lowest $\alpha_{tech,i}$ in the data set. When looking at the fleet's characteristics, this can be explained with the high average distance traveled per trip of 930km, where each tour has an average duration of 12,276 minutes. These trips are out of the range of today's EV battery capacity and full electrification is only possible with intermediate charging stops, which we do not consider.

Limitation of the charging infrastructure In addition to the limited range, we now include the charging infrastructure and charging power. Using the optimization problem described in Section 5.3.3, we determine the optimal charging schedule for each fleet and derive the total number of successful trips. A histogram of all $\alpha_{opt,i}$ values is given in Figure 5.3 (right). As expected, in comparison to the $\alpha_{tech,i}$ a shift towards the left is visible. Compared to the $\alpha_{tech,i}^{med}$ with 95%, the median α_{opt}^{med} is now 9% lower at 86%. With an average of 83%, α_{opt}^{avg} still displays a high potential for fleet electrification.

Overall, by looking at the technical limitations of both the vehicle and the charging infrastructure, we show that there is a high potential for fleet electrification within the REM data set. Nevertheless, complete information to determine a charging schedule is not realistic in the daily operation of a fleet. Therefore, in the next section, we analyze whether heuristics are capable of achieving similar results as $\alpha_{opt,i}$ without the need for complete information.

Table 5.2.: α_{tech}^{avg} for every economic sector

Economic Sector	α_{tech}^{avg}
administrative and support service activities	94%
construction	98%
electricity, gas, steam and air conditioning supply	98%
financial and insurance activities	99%
human health and social work activities	93%
information and communication	93%
manufacturing	94%
other service activities	87%
professional, scientific and technical activities	98%
public administration and defence. compulsory social security	80%
real estate activities	97%
transportation and storage	92%
water supply, sewerage, waste management and remediation activities	94%
wholesale and retail trade, repair of motor vehicles and motorcycles	93%
Overall	**91%**

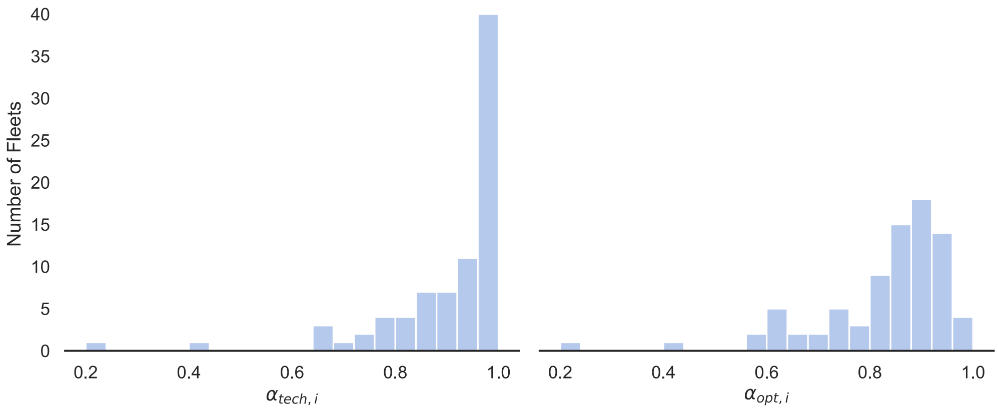

Figure 5.3.: Histogram of $\alpha_{tech,i}$ and $\alpha_{opt,i}$ over all fleets

5.4.2. Impact of heuristic based charging strategies

In this section, we focus on simple rule based approaches to determine a charging schedule for a fleet. In a first step, we determine $\alpha_{base,i}$ as a lower naive benchmark using the First-Come-First-Served heuristic. The results show that with an average of 71%, α_{base}^{avg} is considerably lower than the optimal charging schedule, but still more than two thirds of trips are successful. The same is true for the scenarios $\alpha_{LSOCF,i}^{M,avg}$ and $\alpha_{random,i}^{M,avg}$ with average values of 76% and 71%, respectively. The advantage of Lowest-SoC-First in the manual configuration is based on the possibility to exchange currently charged vehicles with a high SoC, with EVs which are not charged that have a low SoC if a person is on site. Hence, vehicles are less likely to block charging stations after the charge is complete. The random heuristic, on the other hand, can perform both better or worse than First-Come-First-Served. In Figure 5.4, the distribution of fleet α-values for the different heuristics is displayed. The figure shows that even though α drops on average compared to the α_{opt}^{avg}, there are still fleets that perform very well, leading to the question if there are fleet characteristics, which can be used to identify fleets that have a good fit for a heuristic charging approach.

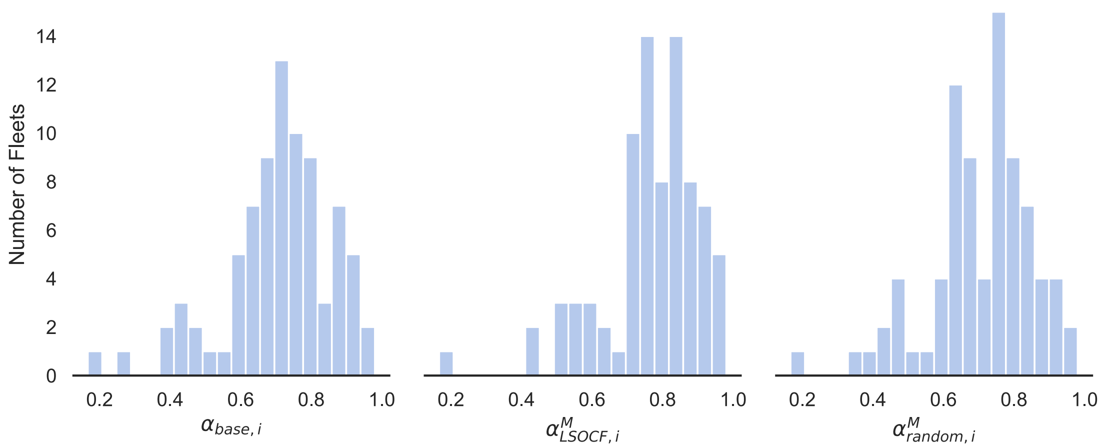

Figure 5.4.: Histogram of $\alpha_{base,i}$, $\alpha_{LSOCF,i}^{M}$ and $\alpha_{random,i}^{M}$ for all fleets

To get a better understanding of which fleet mobility patterns should use which heuristic to perform close to their optimal charging schedule, we use a tree based classification approach with the fleet characteristics introduced in Section 5.3.1 as input features. We assign a class to each fleet, where class "fit" describes all fleets that benefit from a change in their charging strategy by less than 5% and the class "improve" labels the fleets that benefit by more than 5%, leading to the following three classifications $y \in [1, 2, 3]$:

$$C_i^1: \quad \alpha_{opt,i} - \alpha_{base,i} \quad \leq 5\% \tag{5.6a}$$
$$C_i^2: \quad \alpha_{opt,i} - \alpha_{LSOCF,i}^{M} \leq 5\% \tag{5.6b}$$
$$C_i^3: \quad \alpha_{opt,i} - \alpha_{random,i}^{M} \leq 5\% \tag{5.6c}$$

with

$$class_i^y = \begin{cases} \text{fit}, & \text{if } C_i^y \text{ is true} \\ \text{improve}, & else \end{cases} \tag{5.7a}$$

For the classification C_i^1 comparing the $\alpha_{opt,i}$ and $\alpha_{base,i}$ values of individual fleets, 18 fleets are within class "fit" and the remaining 63 in "improve". The resulting classification tree is shown in Figure 5.5 (left). The first split of the tree compares the average trip duration of a fleet. Fleets with a average trip duration shorter than 2899 minutes (48,3h) are most likely to improve if a heuristic smart charging approach other than First-Come-First-Served is chosen. The same applies to fleets with an average trip duration longer than 48 hours, but with more than 0.79 trips per day. On the other hand, fleets with less than 0.79 trips per day have a high probability that First-Come-First-Served is already close to their optimal charging schedule and additional effort into improving their smart charging strategy will not provide large benefits.

In the classification C_i^2 using the manual Lowest-SoC-First heuristic, 31 fleets are within the 5% range of their optimal charging schedule. This indicates that including information on the SoC of vehicles when assigning them to charging stations can have a positive effect on successful trips and that there are fleets that can use this input to reach a close to optimal charging schedule. The classification is shown in Figure 5.5 (center).

Similar to C_i^1, the average trip duration is the main split to classify the fleets when comparing $\alpha_{opt,i}$ and $\alpha_{LSOCF,i}$. However, with 1069 minutes (17.8h) the duration is shorter compared to First-Come-First-Served. Fleets that improve their performance

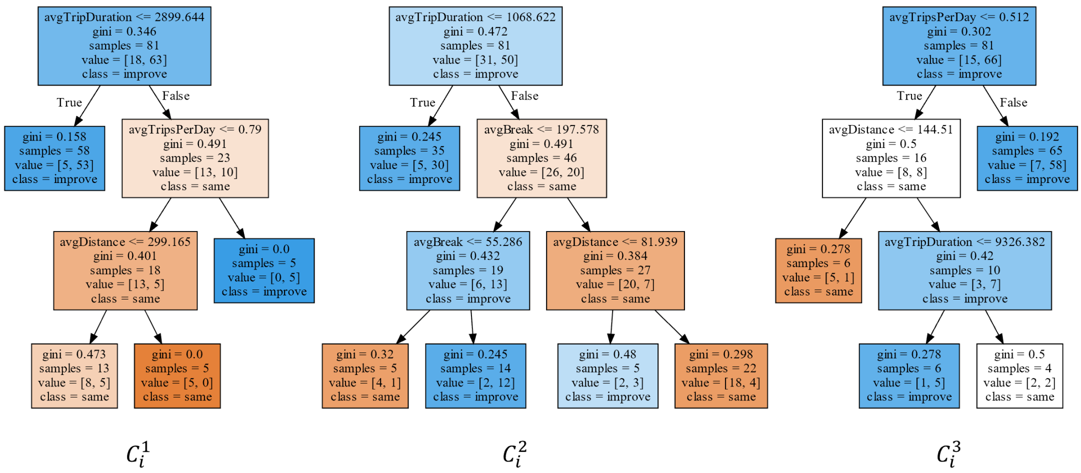

Figure 5.5.: Classification trees using C_i^1, C_i^2 and C_i^2

with a Lowest-SoC-First strategy are characterized by an average trip duration longer than 1079 minutes and an average break longer than 196 minutes or shorter than 55 minutes.

In the last classification C_i^3, we compare the manual random allocation of vehicles to charging stations with the $\alpha_{opt,i}$ benchmark. To incorporate the variance in the results, we repeat the simulation 50 times and use the mean for each fleet as a reference. The decision tree is shown in Figure 5.5 (right). Comparable to the $\alpha_{base,i}$ benchmark, the number of fleets that have a potential for improvement is high with 66 out of the total 81. The only clear cluster identified by the decision tree that does not improve compared to complete information are fleets that have on average less than 0.512 trips per day and travel less than 144km.

The results of this section show that certain fleets have the possibility to apply simple heuristics to operate within a close margin to their optimal charging schedule. Others did not reach their optimal charging schedule and hence have the potential to improve by enhancing their smart charging approach to gain additional successful trips. In the next section, we address two possible approaches to increase these fleets' alphas.

5.4.3. Improvements of charging schedules

In a typical fleet scenario, it is expected that the number of EVs exceeds the number of charging stations. As a consequence, vehicles arriving at the fleet base might not find an available charging station and need to be charged later. In the previous scenarios, this was done manually. Hence, a vehicle can only be reallocated to a charging station if an employee is on site. This can lead to EVs with a fully charged battery blocking a charging station longer than necessary, for example, if the charging session ends at night. From a technical perspective, there are several ways to address this problem. On the one hand, there is the possibility to provide a charging plug for every parking lot and the actual charging capacity can be redistributed among the plugs. In this setup, there is still a limited number of vehicles that can be charged at the same time, but the reallocation of EVs to charging stations is done by a power switch within the charging station and not by moving the actual vehicle. On the other hand, in a future setup with level 4 autonomy, vehicles are able to move freely within a limited space, for example, a parking lot. This allows parking lot operators to summon vehicles to charging stations in an efficient way. Both approaches have their advantages and disadvantages from a technical and financial perspective. As the focus of this work is to evaluate the fit of fleet mobility patterns, we do not elaborate on which approach to choose, but rather on the question if a fleet can profit from automating the power allocation.

Automation - Heuristic Based on the two scenarios *Manual-Lowest-SoC-First* and *Manual-Random*, we now automate the distribution of power to vehicles. In *Automated-Lowest-SoC-First*, this leads to a mechanism that charges the vehicles with the lowest SoC until the second lowest SoC is reached. It then alternates between all vehicles with the lowest SoC. In *Automated-Random*, the mechanism randomly charges a vehicles and reallocates the power every minute. We then classify the benefit of the two charging strategies $y \in [4, 5]$ using

$$C_i^4 : \quad \alpha_{LSOCF,i}^A > \alpha_{LSOCF,i}^M \tag{5.8a}$$

$$C_i^5 : \quad \alpha_{random,i}^A > \alpha_{random,i}^M \tag{5.8b}$$

and Formula 5.7a. The results are given in Figure 5.6.

Overall, the classification struggles with a clear prediction on which fleet mobility patterns benefit from automation based on the characteristics used. We use the Area under the Curve (AUC) to assess the quality of the classification, as it represents the probability of the decision tree to classify a fleet correctly (Hanley and McNeil, 1982). With an AUC of 0.71 and 0.74, the classifiers have the worst performance of all decision trees presented.

In the classification C_i^4 based on the Lowest-SoC-First heuristic, two thirds of the fleets do not profit from the automation. These are mostly characterized by less than 1.127 trips per day. Here, an average vehicle does not do more than one trip per day and has the possibility to charge during the stay at the company base. Charging the vehicles with the Lowest-SoC-First until the next trip appears to be sufficient and automation is not needed. This is also reflected in the average $\alpha_{LSOCF}^{A,avg}$ over all fleets with 76%, which is only 1% higher than the manual counterpart. Fleets that profit from automation have between 1.127 and 1.459 trips per day.

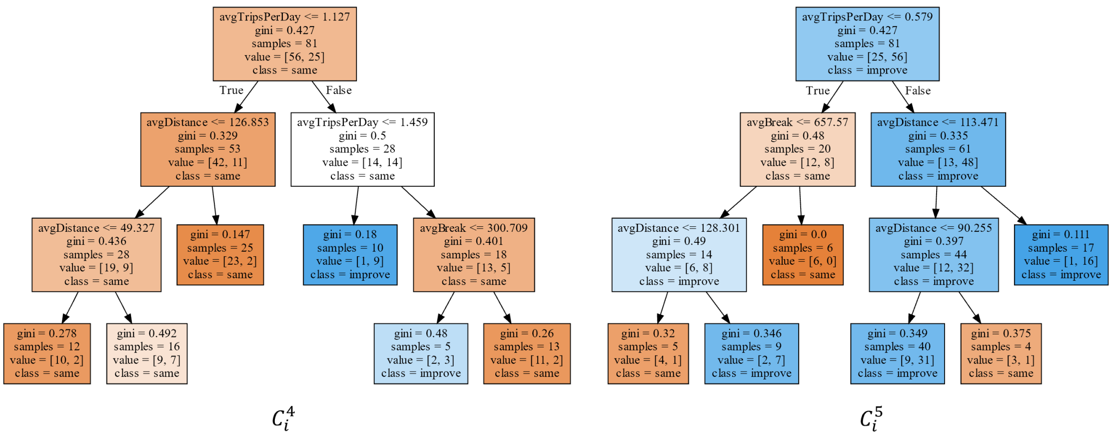

Figure 5.6.: Manual Heuristics compared to their Automated Counterpart

For the classification C_i^5, the average over 50 runs is used as for the manual case to reduce the variation due to the stochastic nature of the results. In comparison to C_i^4, most fleets profit from an automated allocation of EVs to charging stations. The reason why the average alpha only improves by around 1% can be explained by looking at the 25 fleets that did not improve with automation. Due to the nature of the random allocation of vehicles, there is the possibility that the heuristic charges vehicles with a high SoC. In our data set, this leads to 19 fleets performing slightly worse with automation compared to the manual case. The random allocation of vehicles is also reflected in the classification of fleets. Overall, the decision tree struggles to identify sets based on the given characteristics. Two leaves indicate that fleets with very long break times between each trip greater than 657 minutes or trips shorter than 128km cannot improve given that they have less than 0.579 trips per day.

Automation - Foresight The knowledge of future trips varies between different fleets. Whereas some fleets like, e.g. pool vehicles have some sort of booking system that allows them to plan future trips, others, like taxis, have to react almost instantaneously to customer demand. In this section, we focus on the question whether a fleet with given characteristics can increase its potential of electrification by investing into an increased operational foresight, e.g. by introducing a booking system. We classify the benefit of the three charging strategies $y \in [6, 7, 8]$ using

$$C_i^6 : \quad \alpha_{base,i} > \alpha_{foresight60,i} \tag{5.9a}$$

$$C_i^7 : \quad \alpha_{foresight60,i} > \alpha_{foresight360,i} \tag{5.9b}$$

$$C_i^8 : \quad \alpha_{foresight360,i} > \alpha_{foresight1440,i} \tag{5.9c}$$

and the Formula 5.7a.

To this end, we start by looking at the First-Come-First-Served heuristic, representing the scenario where no information on future trips is available and classify a fleet by whether its α_i increases when a foresight of 60 minutes is available (see Formula 5.9a). The decision tree is shown in Figure 5.7 (left).

As expected, the share of fleets that are able to improve by adapting a smart charging approach with 60 minutes foresight is high with 73%. This can be explained by two effects. First, the foresight approach allows a reallocation of vehicles at any minute. Therefore, the probability of fully charged EVs blocking a charging station is reduced. In addition, the foresight approach can use the knowledge on future trips to switch from a simple rule based approach to a demand oriented charging schedule as long as a trip is within the 60 minute time window. The decision tree shows

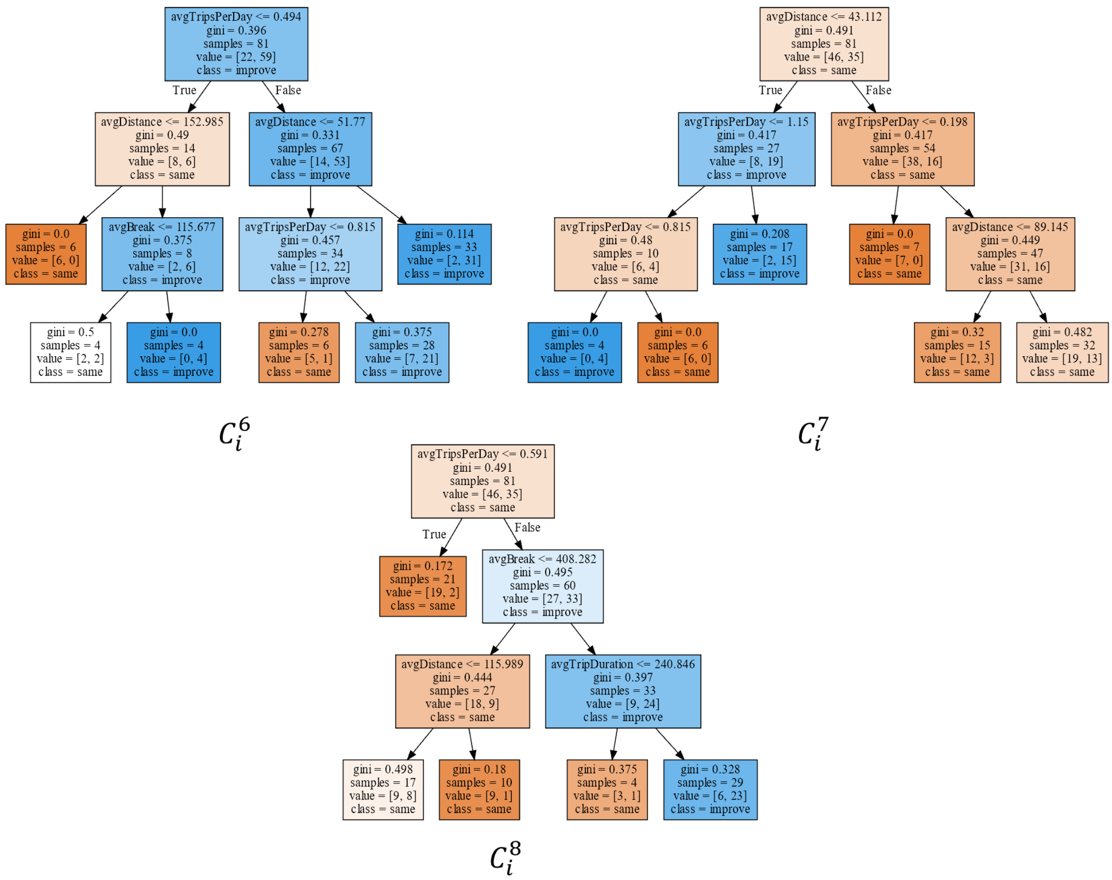

Figure 5.7.: Classification of the Impact of increased Foresight

that there are two clusters of fleets that do not profit from the foresight. The first cluster is fleets with only one trip every two days or less (0.49 trips per day) and an average trip distance of less than 153 km. In this case, the additional information on future trips does not result in more successful trips. This is obvious as few trips without distances close to the upper limit allow for large SoCs at the beginning of any trip. The second cluster are fleets with less than 0.815 trips per day and an average distance shorter 51km. In this case, even though there are more trips per day, the shorter distance allows the First-Come-First-Served to perform as good as the foresight approach.

In a second step, we analyze whether a fleet with a typical foresight of 60 minutes can profit from a 360 minutes foresight. The decision tree is shown in Figure 5.7 (right).

Overall, 57% fleets do not profit from the increase which is a large share considering the increase in foresight. In general, fleets with an average distance greater 43 km are less likely to profit from increased foresight, especially if the average trips per day are less than 0.198 or if the distance is lower than 89km. Fleets that profit from 360 minutes of foresight are characterized by short trips below 43 km and more than 1.15 trips per day. Here, the smart charging approach has the possibility to react to the frequent trips and charge the vehicles according to their needs.

The last classification C_i^8 is an increase in foresight from 360 minutes (6h) to 1440 minutes (24h). Again, 46 fleets do not profit from the additional information on future trips. The decision tree shown in Figure 5.7 (bottom) illustrates the classification of fleets. Fleets that do not profit from a 24 hours forecast are characterized by less than 0.591 trips per day. In addition, an average break time shorter than 408 minutes is an indication that the increase in foresight will not lead to a better result. This might be due to the fact that with an average break time of less than 408 minutes, a smart charging approach with 360 minutes foresight can almost cover the full range of a typical break and therefore utilizes the flexibility of charging sessions. If the foresight is increased to 24 hours, this advantage cannot be exploited, as the vehicle is on the road again.

Fleets that profit form a 24 hour foresight are characterized by more than 0.591 trips per day, breaks longer than 408 minutes and an average distance per trip greater 20km. Here, the optimization can utilize the flexibility of charging schedules.

Overall, the results of this chapter show that operators need to carefully consider whether an investment in increased foresight is valuable. The characteristics presented in Section 5.3.1 are capable to give an indication to which fleet mobility patterns can profit from different charging scheduling strategies. The characteristics mostly used to classify fleets are the average trips per day and average distance per trip. Both characteristics are closely connected to the demand of vehicles and can therefore be used as an indicator for the need of smart charging approaches.

5.5. Discussion

We make several assumptions for our study that we discuss in the following section. First, we only allow the fleets to charge at the fleet base and do not consider public charging. The reason for excluding public charging is twofold: First, we acknowledge that there are commercial fleets where charging along the route is a viable and favourable alternative as the tour might include breaks or stops at a customer site with available charging stations. Nevertheless, a dependency on charging stations not in control of the company represents a risk to the operation of a fleet and might be seen as barrier to EV adoption. Our results therefore represent a lower bound for the potential of successful trips of a fleet that can be further improved on a case by case basis. Here, future research can focus on DSSs that help fleet managers to decide whether to rely on public or private charging infrastructure not only from a technical, but also from an economical point of view. The second reason for our approach is the data set provided by REM2030. Whereas the trips recorded provide a broad range of mobility patterns of companies from different sectors, there is no information on the geographical route of a tour. Hence, it is difficult to identify any charging stations along the tour.

In our study, we define the available grid capacity for every fleet as the minimal power necessary to provide a continuous operation. Whereas from a technical perspective this is a rather restrictive assumption for small fleets, this limitation becomes more relevant with an increasing number of vehicles per fleet. For a company with more than 100 vehicles, providing a 11kW charging station each, leads to more than 1MW of needed grid capacity, which might not be available at the company base. Nevertheless, we acknowledge that an increased grid capacity can have a positive impact on the charging approaches presented in this work and might help to overcome the shortcomings of the simple heuristics.

Regarding the decision tree, we limit the algorithm to three splits to ensure generalizability and to avoid overfitting. It also increases the understandability of the results. Whereas enhancing the number of splits might also increase the AUC and hence the quality of the tree, it reduces comprehensibility. Understanding how the system works can increase users' acceptance of the provided DSS and its results (Gregor and Benbasat, 1999). With the goal in mind of providing a DSS for fleet managers, we chose to use this restriction for the decision tree.

We propose two approaches to improve the number of successful trips of a fleet, automation and foresight. The automation of the EV charging is a rather new technology and is not widely adopted. We assume no cost for reallocating EVs and the switch is instant. This might not be the case for every technical implementation. Nevertheless, the results identify fleets where even an automation system without cost and time restrictions does not provide a benefit.

The foresight analyzed in this study allows the charging schedule to be adapted to future trips. Due to computational constraints, a rolling optimization horizon is not feasible and hence, an iterative process is implemented. This leads to a scenario where the foresight represents an upper bound at which information of trips is available. There is a possibility that the reaction time of the charging schedule is reduced if a trip starts shortly after the previous foresight period. Even tough this is a limitation of the simulation, it is in line with our argumentation that the results represent a lower bound of successful trips.

Finally, we want to point out that even though the data set covers companies from different sectors, they are regionally restricted to Germany. Special circumstances prevalent in other countries are therefore not considered.

5.6. Conclusion

In this study, we show that there is a technical possibility to electrify a large share of commercial fleets. In addition, we provide decision support for fleet managers that plan to electrify their fleet to choose the most effective charging approach that still allows a large share of successful trips being performed by an electrified fleet. This analysis includes the possible automation of charging sequences and the exploitation of operational foresight. To answer Research Question 3, the optimal charging schedule for every commercial fleet within the data set is calculated. The results demonstrate that from a technical perspective, 83% of analyzed fleet trips can be electrified when considering technical limitations of the vehicle and charging infrastructure. We show that for certain fleets, heuristic charging strategies can lead to a close to optimal charging schedule. We design a decision support system that helps in identifying fleets where an improvement in the charging strategy can be expected to yield a gain in operations. Within the heuristic approaches, using the Lowest-SoC-First heuristics is the most successful charging approach. Fleets that reach their technical potential using the Lowest-SoC-First heuristic are characterized by long trip duration followed by an average break of more than 197 minutes, where the distance covered per trip is higher than 81km. Besides the heuristic approaches, we also provide decision support on whether the number of successful trips of a fleet can be improved through the implementation and development of automation or foresight. Whereas the improvement due to automation of charging sessions is most visible for the random heuristic, the results show that on average, the Lowest-SoC-First heuristic without automation performs better than random automatized charging. The influence of foresight is especially visible when comparing the First-Come-First-Served heuristic to an optimization strategy with one hour of foresight. Here, 73% of fleets are able to increase the number of successful trips. The average break time becomes relevant when increasing the foresight from 6 hours to 24 hours. A summary of the main findings is given in Figure 5.8. With regards to Research Question 3, this chapter introduces a DSS that identifies the conditions under which a fleet is able to be electrified based on their mobility patterns. In conclusion, we show that an electrification of large parts of commercial fleets is possible from a technical perspective, thus contributing to a carbon emission reduction in the transportation sector.

The setup analyzed in this chapter describes a lower benchmark as charging is only possible at the fleet base. By looking at charging stations along the route, the number of successful trips can be improved even further. This is especially relevant for fleets that are continuously in operation or that are exposed to uncertainty of trip length. Such a use case is addressed in the following chapter.

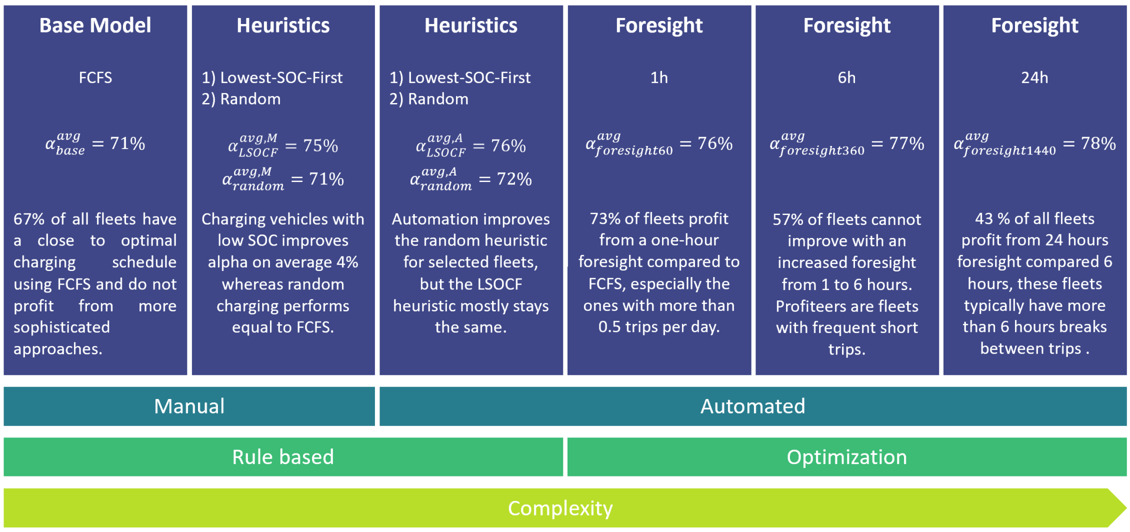

Figure 5.8.: Overview scenarios and main results

Chapter 6.

Public Charging of Electric Taxis

Although it is preferred to charge commercial fleets at places where they usually park (Al-Hanahi et al., 2021; Nadel and Junga, 2020), there are still reasons to charge along the route. One of the main disadvantages of the depot based charging approach is that the fleet can only operate in a radius of half the vehicle's range, as the other half is needed on the return trip. Consequently, EVs in commercial fleets operating from a depot ought to have large batteries to meet the required range (Al-Hanahi et al., 2021). For every tour that exceeds this limited radius, access to public charging infrastructure is required. This is also referred to as opportunity charging and generally occurs between shifts or during breaks and stopovers (Earl et al., 2018). As a consequence, it is important to provide public charging stations at locations included in the mobility patterns of commercial fleets. The challenges of this matter are further analyzed in this chapter.

6.1. Introduction and Related Work

Public charging infrastructure provides the benefit of distributed locations to recharge EVs. However, it comes with its own challenges, especially for the operation of a commercial fleet. By definition, public charging infrastructure is not in possession of a fleet and consequently fleets depend on a third party to build and operate the necessary charging stations. Whereas private charging infrastructure, as shown in Chapter 5, can be scaled to fit the fleet's demand and charging strategies can be applied to prioritise vehicles to improve operation, this is not the case for public charging stations. In addition, commercial fleets do not have a direct influence on the location of public charging stations and therefore have to plan their trips in advance in order to utilize charging stations along the route. Furthermore, there is a competition for charging infrastructure, as other fleets can use the same location at the same time for recharging.

Whereas most of these challenges also apply to private EV users that depend on public charging stations, commercial fleets have a unique challenge linked to their vehicles. Considering that private EV users typically operate standard passenger cars, there is a wider diversity in the challenges of commercial fleets due to specialized vehicles. For instance, vehicles with trailers might not be able to access every charging station as a result of their size. The same can be said about trucks, busses or other large scale vehicles. As a consequence, this quadrant of the matrix illustrated in Figure 1.1 is characterized by a broad sample of use cases, each with its own challenges.

Short-haul commercial electric vehicles Fleets that mainly consist of short-haul trucks have the potential to utilize public charging stations within their area to increase range during operation. Due to the different requirements for power and site access, these public charging stations need to be considered separately. Whitehead et al. (2021) show that public charging infrastructure for short-haul electric trucks is important to foster confidence in this new market. Further they show that the range of short-haul trucks is sufficient for most trips but only a modest network of public charging stations is required. Consequently, most charging sessions will be conducted at the depot, as analyzed in Chapter 5.

Long-haul commercial electric vehicles Long-haul logistics is highly energy intensive and therefore has a great potential to reduce GHG emissions when using electric trucks (Utomo et al., 2020). Electric long-haul trucks ideally charge en route at rest stops and consequently, characteristics of the fleet's operation determine the required charging power (Nadel and Junga, 2020). Especially for large trucks this translates into very high charging power that constitutes an extensive challenge for the grid, particularly when multiple trucks are charged at the same location (Earl et al., 2018). In such a scenario, the focus of fleet electrification shifts towards a technical implementation capable to provide high power to every truck rather than applying smart charging approaches due to the time-critical operation of such trucks. As an example, the authors of (Bischoff et al., 2019) provide an overview on the distribution of energy consumption in Sweden due to electrification of long-haul trucks. Their results show that especially along highways, a high demand for public charging infrastructure arises. This focus on high charging power does not only define the requirements for the charging infrastructure, but also for the battery within trucks. For opportunity charging of commercial vehicles, the battery needs to be power-optimized, meaning they can be charged in a very restricted time period (Earl et al., 2018). Due to the technical peculiarities of long-haul truck electrification and the limited flexibility provided by the fleets, this use case is not further analyzed in this thesis. The interested reader is referred to Kluschke et al. (2019) for a review on the market diffusion of alternative fuels heavy-duty vehicles and to Cunanan et al. (2021) for a technical review of heavy-duty vehicle power train technologies.

Electric Taxis and Ride Hailing Whereas the short and long-haul commercial fleets focus on transporting goods, there are also fleets that meet the transportation demand of people. In this context, traditional taxis and online car-hailing describe an on-demand shared or public transportation service that provides daily mobility convenience for residents (Lyu et al., 2021). In comparison to public transport, they do not follow a fixed schedule and adapt to customer needs. From an environmental perspective, electric taxis can provide benefits. Especially due to their high driving distance, electric taxis can help to reduce air pollution in crowded urban areas (Cilio and Babacan, 2021). Consequently, electric taxis have a great potential to contribute to the goal of GHG emission reduction. The high mileage also has an impact on the cost of operation. As electricity is cheaper than fossil fuels per kilometer, a switch to an EV can reduce the fuel expenditures of taxi drivers (Hu et al., 2018).

The operation of taxis is characterized by uncertainty on future trips. Due to the absence of a schedule and dependency on short-term user requests, the mobility pattern of taxis varies every day. Whereas taxis might start their shift from a depot with a fully charged battery, there is no guarantee that their range is sufficient for the entire day. As a consequence, electric taxis are depending on a public charging infrastructure (Funke and Burgert, 2020). Whereas Chapter 4 demonstrates that for private EV users, slow charging can be sufficient to charge the vehicle within the week, this does not apply for taxis. Here, due to the high mileage of the vehicles and the potentially lost revenue do to the time spent charging, a city-wide network of fast charging stations is required (Cilio and Babacan, 2021).

Besides the technical requirements for electric taxis and the public charging infrastructure, there is also the need to analyze the economical impact of taxi electrification. The user of an electric taxi is not the customer, but the driver and therefore, the main objective of taxi electrification is to allow a switch towards EVs without a negative impact on revenue. In their work, the authors of Funke et al. (2015) show that whereas there are multiple papers analyzing the technical requirements of electric taxis, the research on techno-economic analysis is rare. This Chapter contributes to this research gap by focusing on empirical taxi data from Chicago to provide insights on how different charging strategies can impact the operational revenue of different taxi mobility patterns.

6.2. Method

Within this chapter, a simulation of electric taxis is introduced. For a detailed representation of today's mobility pattern, in a first step, the empirical data is presented. Afterwards, an overview of promising charging strategies is given.

6.2.1. Data

In order to analyze the user behavior of taxi drivers in Chicago, there is a need for both empirical data of trips that occurred within the city as well as information on the existing charging infrastructure. The used data sets are described in the following.

Taxi Trip Data The city of Chicago provides a public data set of historic trips of taxis operating within the metropolitan area through the *Chicago Data Portal* (Chicago, 2021). The data set contains more than 193 million individual trips covering a range from January 2013 until today. The information associated with the trips covers, for example, the census tract where the trip starts and ends, the start and end time as well as the distance traveled. Due to privacy issues, the data set is anonymised and no exact GPS data is provided.

The data set is not complete and for certain trips information might be missing. In addition, there are recordings that are not viable. To address this issue, as a first step, the data is prepared for the simulation. Trips without any geo-specific data cannot be used within the simulation and are therefore removed from the data set. Further, trips with unrealistically long traveling time and distance are removed. For the cutoff, 90 minutes and 64.3km (40 miles) are used. These values describe to longest possible trip duration and distance within any census tract in Chicago (Chen et al., 2018). For trips with missing information on the distance traveled, the air-line distance from the start to the destination is calculated and multiplied with the factor 1.4. This factor is derived from a random selection of 100 trips within the data set, where the ratio of air-line to actual distance is known.

Overall the data set contains 1.12 million trips and 4207 vehicles. An overview of the distribution of trips throughout a day and within a week as well as the distribution of the length of individual trips of taxis is illustrated in Figure 6.1.

City of Chicago The city of Chicago is split into 866 census tracts that define small areas with homogeneous characteristics and typically include around 1200 households (UChicago, 2021). The differentiation by census tract is used to provide detailed information of the start and end of a trip, while considering the privacy of taxi drivers and customers. Besides information on the trips of taxis and the area of Chicago, there is also a need for data on the existing charging infrastructure within the city. To find the exact locations of charging stations within the census tracts, the TomTom API is used (TomTom Developer Portal, 2017). In total, the API returned 262 charging stations. An overview of all census tracts and the charging locations considered within the simulation is provided in Figure 6.2.

Vehicle The reference vehicle used in this simulation is a Tesla Model 3. The reason for this choice is the number of sales of this vehicle (Wilkens, 2021) and that it is a proven option for electric taxis (Yao and You, 2020). In addition, the Tesla Model 3 is already in operation as a *Yellow Cab* in New York (Lambert, 2021). The Tesla Model 3 has a total of 47,5kWh of usable battery capacity and an average consumption of 15kWh/100km (EV Database, 2021). Consequently, the expected

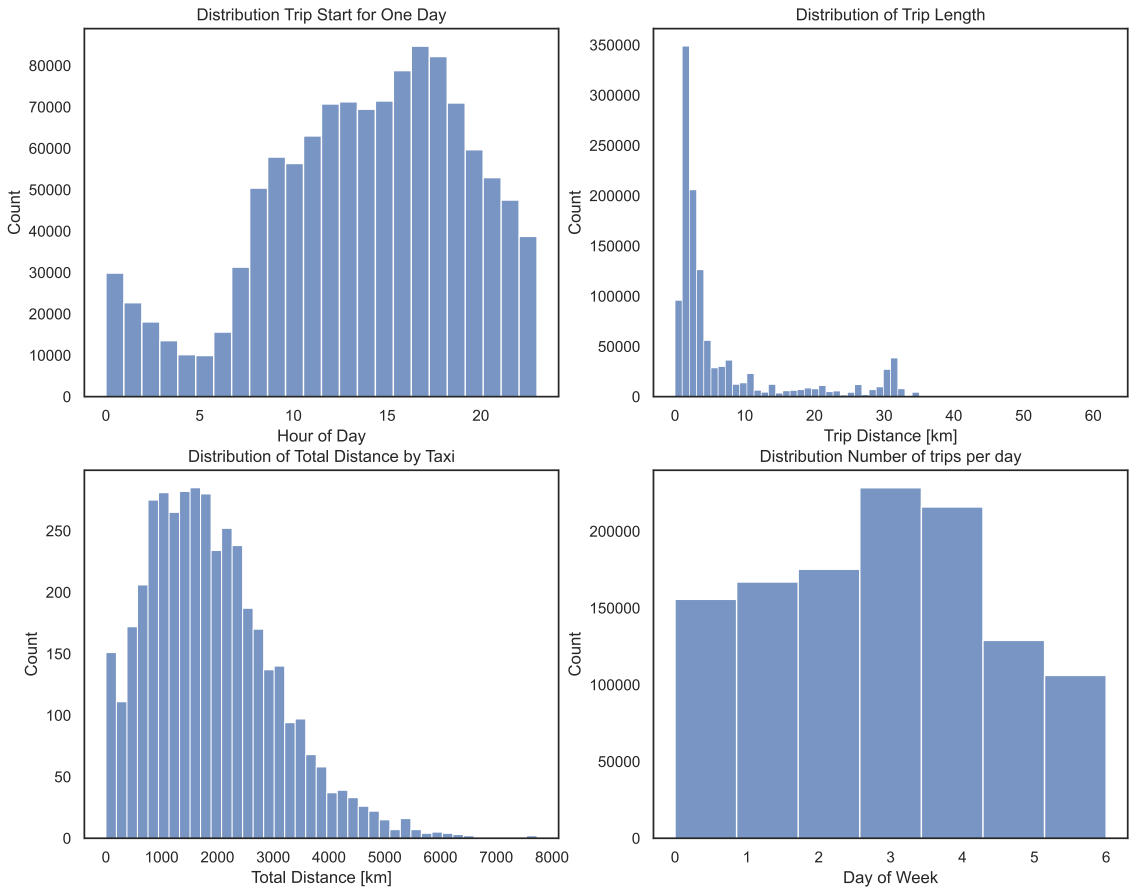

Figure 6.1.: Taxi Travel Pattern in Chicago

range is set to 315km. An overview of the vehicles characteristics is provided in Table 6.1. As a reference consumption for ICE based taxis, the authors of Wu et al. (2017) show that taxis within Beijing have a typical consumption of 9.49 L/100km, which is therefore used in this simulation. For the economic evaluation, a cost of €0,45 per kWh (EnBW, 2021) and €1,37 per liter diesel (Statistisches Bundesamt, 2021) are assumed. This results in a total of €6,75 per 100km for EVs and €13,00 for ICEV.

6.2.2. Charging Strategies

The central decision during the operation of electric taxis is the choice of when and where charging sessions should be initiated. There can be a set of rules that trigger a charging session that as a whole define a charging strategy. Once one of the triggers

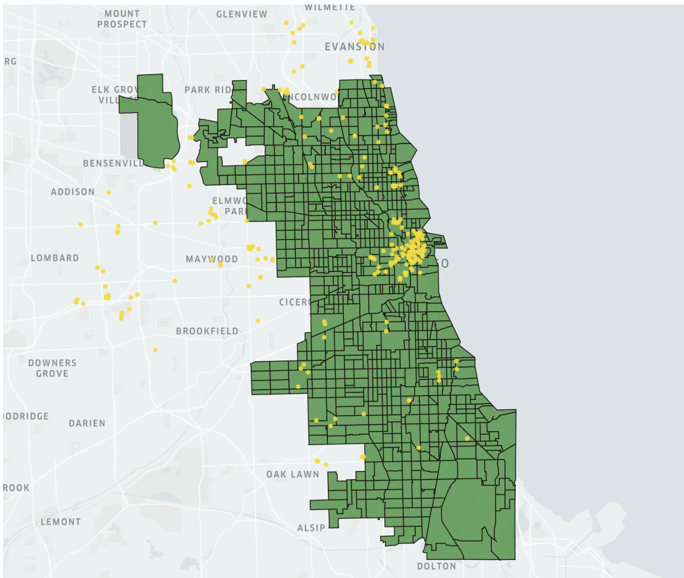

Figure 6.2.: Census Tracts and Charging Locations in Chicago

Table 6.1.: Characteristics of a Tesla Model 3

Parameter	Value
Battery capacity	50
Usable Battery capacity	47.5
Consumption [kWh/100km]	15
AC Charging Speed [kW]	11
Maximum Range [km]	315

within a charging strategy is set off, the taxi will start the search for a charging station. Within this section, possible triggers are defined and the resulting charging strategies are presented.

Low State-of-Charge The first trigger is referred to as T_{lowSOC} and is based on the refueling behavior of current ICEVs. Similar to ICEVs that visit a refueling station once the tank is depleted, electric taxi drivers can charge their vehicle as soon as a lower threshold of their SoC is undercut. Within this work, the threshold is set to 20%. In order to minimize the distance traveled, it is assumed that electric taxis drive to the closest charging station and completely charge their vehicle.

Long break In a typical operation, taxis are not in movement for a full day, but rather operated in shifts. Once a shift is over, a taxi driver has a longer break that can be used to recharge the EV and is referred to as trigger $T_{longbreak}$. This trigger assumes that the taxi is able to charge at the location it is parked at, such as a taxi depot or the private home of the taxi driver.

Avoid Rush Hour As shown in Figure 6.1, the number of trips is not distributed equally throughout the day. Therefore, charging sessions within the off-peak traffic might have a lower chance for lost revenue. Consequently, electric taxis can shift charging sessions into off-peak periods, which is referred to as Trigger $T_{offpeak}$. For this trigger, a threshold of 50% is used to define a minimum SoC a taxi has to have within the off-peak period, which is higher than the one of T_{lowSOC}. Using this threshold avoids unnecessary charging sessions in the off-peak period of vehicles with an already high SoC.

Hotspots This trigger relies on an additional assumption on the charging infrastructure. As shown by the authors of Cilio and Babacan (2021), there are locations with a high potential for taxi charging infrastructure. These locations are referred to as hotspots and are defined as the locations with the most starts of trips. It can be assumed that those locations are within the first to install charging infrastructure. Consequently, the trigger $T_{hotspot}$ is activated once a taxi visits a hotspot.

It has to be acknowledged that those triggers might not be available for every taxi as some might not have the ability to charge at home or at the depot. Nevertheless, the objective of this analysis is to determine promising charging strategies for electric taxis based on their mobility pattern using the triggers described above. The results can then be used to adapt the EV ecosystem to benefit electric taxis, such as providing charging infrastructure at the driver's home (see $T_{longbreak}$) or by installing additional charging stations at promising locations (see $T_{hotspot}$).

In the next step, this set of triggers is used to define charging strategies. There are three basic charging strategies that are used to determine the potential of public and

Table 6.2.: Overview of Basic Strategies and Extensions

Strategy	Triggers
S_{public}	T_{lowSOC}
$S_{private}$	$T_{longbreak}$
S_{combo}	T_{lowSOC}, $T_{longbreak}$
$S_{offpeak}$	T_{lowSOC}, $T_{longbreak}$, $T_{offpeak}$
$S_{hotspot}$	T_{lowSOC}, $T_{longbreak}$, $T_{hotspot}$

private charging infrastructure as well as the combination of both. The first strategy S_{public} is exclusively combined with trigger T_{lowSOC} and defines a baseline for electric taxis without the possibility to charge at home or at a depot. In this setup, electric taxis are only charged at public charging stations within the city of Chicago while in operation. The second strategy $S_{private}$, in contrast, defines the baseline for electric taxis that avoid public charging stations at all cost. In this strategy, combined with trigger $T_{longbreak}$, taxis only charge at home or at a depot during long breaks. In the case that the SoC is not sufficient throughout the day, the driver returns home and does not serve any other customer request. The third strategy S_{combo} is combined with triggers T_{lowSOC} and $T_{longbreak}$ and describes electric taxis with a possibility for private charging that also utilize public charging stations if necessary.

These basic strategies are complemented with additional two charging strategies that explore the possibilities of electric taxi drivers to optimize their charging sessions as well as possible infrastructure extensions. Charging strategy $S_{offpeak}$ extends S_{combo} with trigger $T_{offpeak}$. In this strategy, electric taxi drivers use their knowledge of historic trips to charge the EV in times of low workload. In addition, charging strategy $S_{hotspot}$ extends S_{combo} with the trigger $T_{hotspot}$, assuming that adequate charging infrastructure is provided at the hotspots. A complete overview of the charging strategies is presented in Table 6.2.

6.2.3. Simulation

Within the simulation, the driving pattern of each individual taxi is analyzed. Based on the trip data of a taxi, in a first step, all the relevant trips are extracted. The simulation begins at the start location of the first trip with a taxi that is fully charged and follows each individual trip as long as the SoC of the vehicle is sufficient. Once one the the triggers defined in the charging strategy is activated, the taxi locates the closest charging station within the city of Chicago and starts charging. All the trip requests during this time are ignored and the lost revenue is logged. Once charging is completed, the taxi continues to accept trip requests. This procedure is repeated for every taxi within the data set. The simulation then returns the distribution of successful trips, the revenue a taxi achieved and lost as well as the total distance traveled. As a result, the simulation also returns the change of cost for operation, defined as the difference between the cost saved on fuel subtracted by the lost revenue due to missed trips. These results are further analyzed in the subsequent section.

6.3. Results

Within this section, the distribution of the share of successful trips among taxis is analyzed for each charging strategy in order to identify their strengths and weaknesses. In addition, the operational savings or expenditures associated with the switch to an EV are quantified in order to answer Research Question 4.

Over all charging strategies analyzed in this chapter, the share of successful trips by electric taxis is high, but their distributions differ. The complete distribution of the share of successful trips for each charging strategy is illustrated in Figure 6.3.

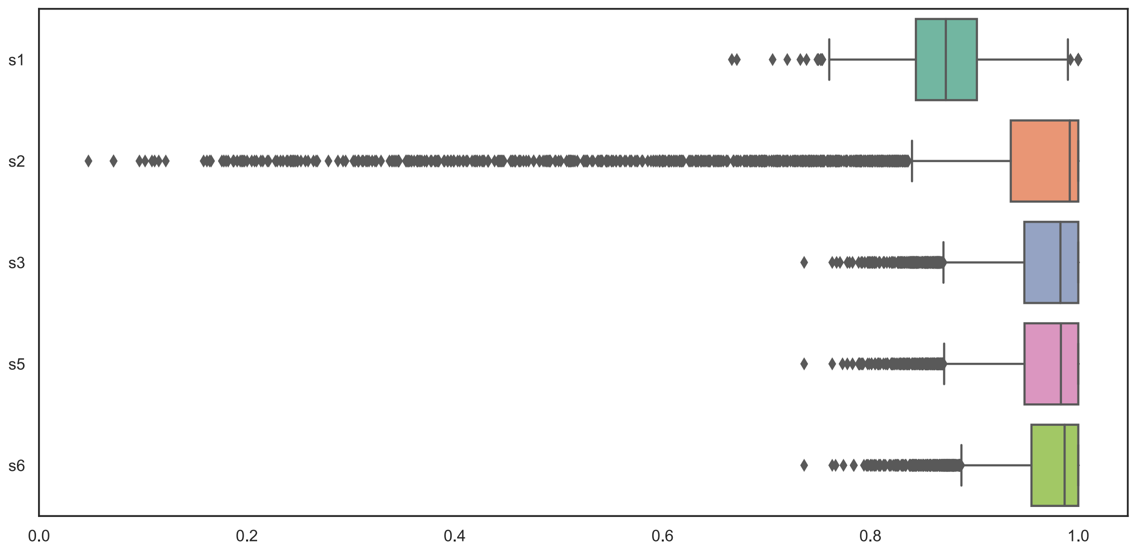

Figure 6.3.: Distribution of Success Rate of Individual Taxis

Starting with S_{public}, where taxis only rely on public charging infrastructure, the average taxi completes 87% of its trips. Whereas this can be considered high, it is the lowest out of the charging strategies. In comparison, $S_{private}$ and S_{combo} have an average share of successful trips of 92% and 96%, respectively. This is in line with current research, as charging at home or at a depot describes a comfortable approach to charge a taxi outside of business hours. Due to the exclusive use of depot charging in strategy $S_{private}$, the number of outliers with low success rates is high.

Within the two additional charging strategies, $S_{hotspot}$ provides better results when compared to $S_{offpeak}$. Whereas a direct comparison cannot be done due to the different charging infrastructure used in these charging strategies, the results still provide important insights. First, when looking at strategy $S_{offpeak}$, there is only a negligible difference compared to S_{combo}. Here, the quantiles, the average and mean are almost identical, which indicates that charging outside of peak periods does not improve the success rate of electric vehicles. Providing charging infrastructure at taxi hotspots, on the other side, does provide a benefit with an average success rate of 97%, which is the highest out of all strategies.

Taxis are operated on a profit-basis and therefore, missing trips can be compensated if there are other monetary gains associated with the adoption of EVs. In the context of taxis, this is the case with the cost for fuel and electricity. As a consequence, the objective is to have higher savings through fuel cost reduction when compared to the lost revenue due to missed trips. This is referred to as operational return. The distribution of this operational return is illustrated in Figure 6.4 and 6.5. The data shown in Figure 6.4 is limited to the range of €-1500 to €350 for better visibility and therefore, strong negative outliers are not shown. For a complete picture, Figure 6.5 shows a cumulative distribution for the complete range of results.

In line with the findings for the success rate, the results demonstrate that the strategy S_{combo} shows better results than $S_{private}$ and S_{public}. Using strategy S_{public}, only 6.7% of electric taxis can operate with a profit, with an average operational return of €-351.88. In comparison, when charging only at private charging stations with strategy $S_{private}$, 71.0% of taxis have a positive operational return with an average of €-296.05. The negative average operational return can be explained with the outliers within the results. As already shown in Figure 6.4, there is a large group

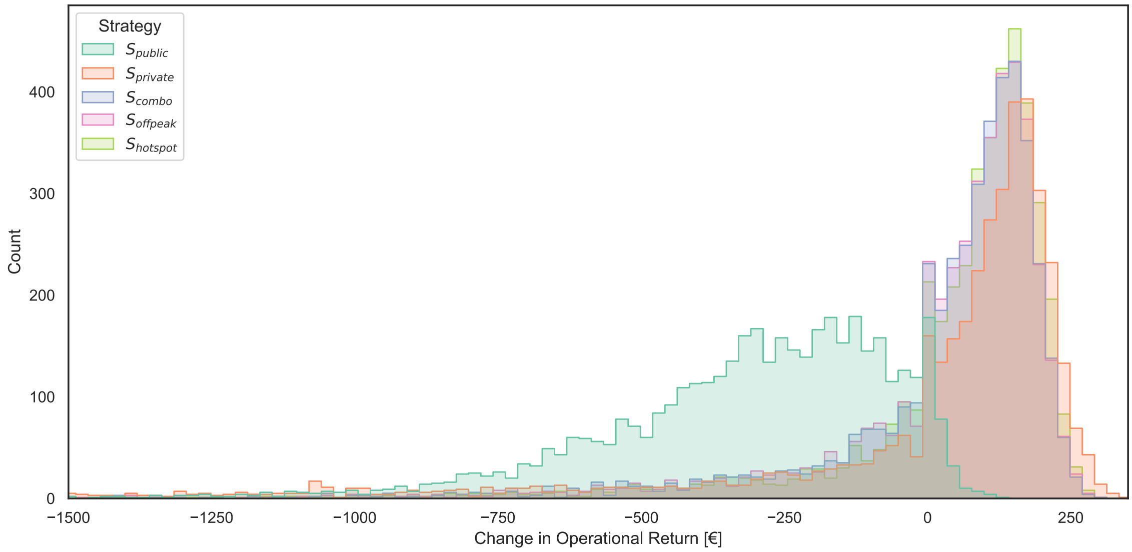

Figure 6.4.: Distribution of Operational Return of Electric Taxis

of taxis that cannot meet their demand without charging at public charging stations. This results in a minimum operational return of €-9700.61 using strategy $S_{private}$ compared to €-5221.30 using strategy S_{public}. In comparison, charging strategy S_{combo} combines the advantages of both strategies and consequently has the largest share of taxis with a positive operational return with 75.7% and an average of €-12.67.

Within the two additional charging strategies, $S_{offpeak}$ and $S_{hotspot}$, the operational return is increased even further. Using charging strategy $S_{offpeak}$, 76.2% of taxis have a positive operational return with an average of €-10.03, which is slightly higher for S_{combo}. Strategy $S_{hotspot}$ provides the best results with 79.5% of taxis having a positive operational return and in addition, it is the only strategy with a positive average operational return of €9.01.

Regarding Research Question 4, the results of this simulation show that depending on the charging strategy, a range of 6.7% to 79.5% of taxis can be electrified with a positive impact on the operational return. Further, the results highlight the importance of both public and private charging infrastructure for taxi fleets. With strategy S_{combo}, 75.7% of taxis can operate with a positive operational return using the existing charging infrastructure in Chicago.

In addition, the results demonstrate that for further improvements, the installation

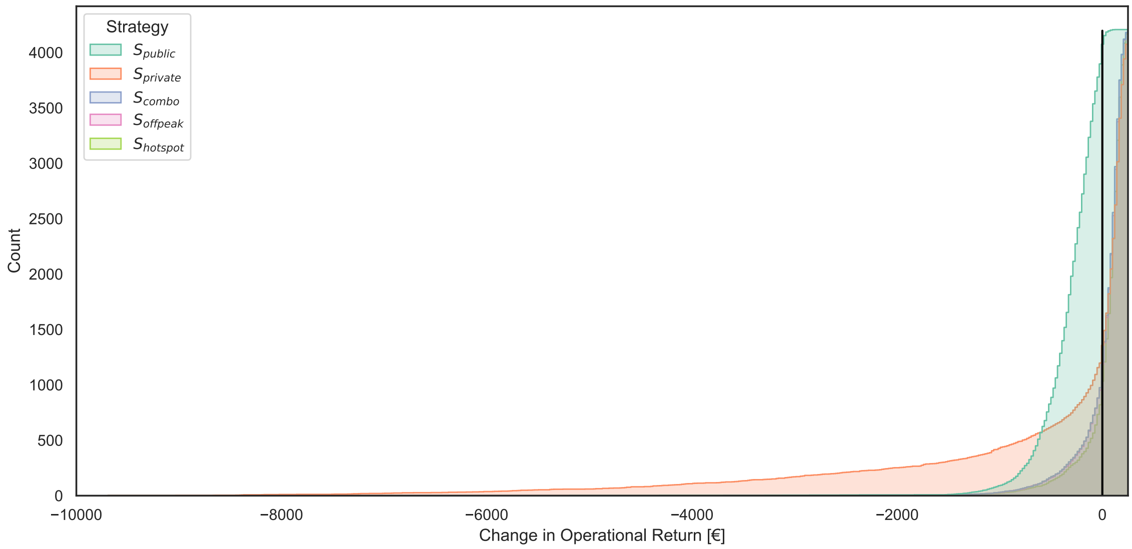

Figure 6.5.: Cumulative Distribution of Operational Return of Electric Taxis

of charging stations at hotspots is a promising approach, which shows the best results within the simulation. Charging outside of peak hours, on the other hand, only had a small impact.

6.4. Discussion

The simulation in this chapter analyzes the impact of an electrification of taxis in Chicago based on empirical data. Whereas the trips reviewed describe the actual user behavior of taxis, there are several limitations to this approach, which are discussed in the following. The chain of consecutive trips within the data set assumes a continuous operation. Once a taxi stops for a charging session, it moves to a different location and therefore might be exposed to different trip requests. This cannot be integrated within the empirical data. Additionally, the simulation does not include blocked charging stations due to other taxis or private EV users. Whereas most locations provide multiple charging stations, it is not clear if every charging session can immediately be started. Here, further lost revenue due to queuing can occur. Nevertheless, the results show that from an operational perspective, taxis have a great potential for electrification given the right charging strategy. Especially considering their positive impact on the environment, the electrification of taxis should be encouraged.

6.5. Summary

In this chapter, an agent based simulation to analyze the potential of electric taxis is introduced. Building upon the findings of Chapter 5, the simulation analyzes both the exclusive usage of private and public charging infrastructure, as well as their combination and two extension based on foresight and infrastructure development. Using empirical data from Chicago, the results demonstrate that given the right charging strategy, a large share of taxis can be transformed to EVs while creating a positive impact on their operational return. Whereas the exclusive charging at the depot on average creates a better result compared to exclusive charging at public infrastructure, the spread of the share of successful trips increases. To answer Research Question 4, the combination of both private and public charging stations is optimal. The results demonstrate that a total of 75.7% of taxis experience a positive impact on their operational return when switching from an ICEV to an EV. This represents a large potential for electrification and should therefore be explored further. Using the two additional charging strategies $S_{offpeak}$ and $S_{hotspot}$, the simulation provides additional management insights. Whereas charging the taxi outside of peak demand provided no advantage, the installation of additional charging stations at hot spots had a strong positive impact on the operational revenue of taxis. City officials as well as CPOs can profit from this finding and consequently provide additional charging stations at frequently visited locations.

Overall, this part demonstrates that even though commercial fleets vary in their operation, there are still possibilities to include their mobility patterns in the charging strategy. Chapter 5 establishes that using private charging stations at fleet depots only, can already cover a large share of trips. Further, Chapter 6 demonstrates that while charging during operation can have a negative impact on the income, the gains of switching to an EV can compensate the losses and even create a positive impact on the operational return. The findings of this part are bound by the technical possibilities of EVs and charging infrastructure available today. However, the results also demonstrate that applying technological improvements, such as automated reallocation of vehicles, has the potential to improve the results even further and should therefore by analyzed in more detail. Consequently, the next part will look ahead into a scenario, where automated vehicle can be utilized to improve users' comfort.

Part IV.

Automated Charging

Introduction to Part IV

Within the two previous parts, the potential of available charging infrastructure and vehicles is analyzed to develop charging strategies that consider the current mobility patterns of users. Besides the advantages of integrating charging sessions into users' current mobility patterns, the results also demonstrate that charging strategies still have the potential to be improved. In Chapter 4, as an example, a framework to determine the losses of demand is introduced. The case study demonstrates, that both users of EVs as well as CPOs are negatively impacted from blocked charging stations. However, owners of EVs are unwilling to move their vehicle after a charging session is completed (Philipsen et al., 2016) and consequently, new solutions are needed to address this issue. Here, automated vehicles that can relocate without any input from the driver can help to provide comfort to users while providing economical advantages to the CPOs. An automated vehicle can, for example, reduce the *Occupancy Loss*, as defined in Chapter 4 or help fleet managers to introduce the automated charging strategies introduced in Chapter 5. In Part IV, the potential of autonomous driving to solve the challenges identified in fitting strategies to the user's behavior is analyzed. One example of autonomous mobility is automated valet parking, where users are no longer required to move their vehicle after a charging session is completed. Using the sensors of the vehicle or the car park, EVs can be relocated to follow a predefined charging schedule. This part identifies approaches to determine such a schedule in real time and further extends the provided services beyond charging an EV. In conclusion, this part provides an outlook on the potential of automated valet parking and identifies possibilities to improve the user experience while charging in the long-run.

Chapter 7.

Scheduling Services for Automated Valet Parking

Automated valet parking (AVP) allows drivers to hand over the vehicle at the entrance of a destination, such as a car park, and leave, while the vehicle parks itself. This provides comfort to users, but also allows car park operators or CPOs to relocate the vehicle on demand and consequently, to provide services such as charging, while at the location. Within this chapter, a platform based on AVP is introduced to schedule charging sessions, which is then extended to include other services, such as washing the vehicle or receiving deliveries into the trunk. Due to the necessary real-time online operation of such a platform, a novel extension of the Job-Shop Problem is introduced. Using constraint programming, a valid schedule is determined and improved within the time constraints of the car park. It is further benchmarked against two heuristics to gain insights on the quality of the results as well as its ability to scale. This chapter comprises the results of the working paper (Schmidt and Staudt, 2022) currently under review at the *European Journal of Operational Research* and is joint work with Philipp Staudt.

7.1. Introduction

Autonomous driving will make problems with parking a thing of the past. Beginning with level 4 autonomy (SAE International, 2021), the driver does not need to control the vehicle in controlled environments (Wang et al., 2021) and hence, can either pursue different tasks or leave the vehicle. Autonomous vehicles (AV) can increase social welfare, promote shared mobility and and increase accessibility of low-income households to mobility (Baron et al., 2021). It can also decrease transportation costs (Bagloee et al., 2016). It should therefore be facilitated into today's mobility mix.

Automated Valet Parking (AVP) is considered the first use case for AVs (Banzhaf et al., 2017) and is currently being tested and demonstrated in multiple pilot projects, such as at the International Auto Show in Germany in 2021 (VDA, 2021). There are several advantages associated with AVP, such as the ability to move vehicles whenever necessary (Zips et al., 2020), saving the time needed to search for a parking lot (Schuß and Riener, 2020) and the potential to reduce the space occupied per vehicle (d'Orey et al., 2016). This has lead to different potential use cases where AVP can increase the comfort of drivers, such as on arrival at an airport (Bosch, 2020) or as a seamless transition to public transport (Scholliers et al., 2020).

An average vehicle is parked more than 23 hours per day (Nobis and Kuhnimhof, 2018). During this time, it is not generating any benefit for the owner. With AVP, vehicles are mobile even without the driver being present, which allows the system to move the vehicle to different spots within the parking lot. As a consequence, vehicles are capable of attending different service stations and fulfill tasks (e.g. picking up ordered goods).

In this work, we introduce Automated Valet Parking Services (AVPS), which are fully automated services that vehicles can book and that can be performed while the vehicles are located at a car park. Examples for AVPS are the delivery of goods, a cleaning service such as a car wash or repairs of the vehicle itself. Further, AVPS can also be seen as a support to electric mobility. With an increasing number of electric vehicles (EVs) on the road, the demand for comfortable charging solutions increases. AVPS can provide this comfort by allowing EVs to charge while located at the parking lot. Besides comfort for customers, AVPS also provide a benefit to the service station operators, like CPOs, as vehicles do not block the station after the service is performed as they can be relocated to a different parking space, which can result in higher utilization of the infrastructure.

This benefit has been addressed in several research projects, such as the European research project V-Charge (Schwesinger et al., 2016) and AutoPles (Klemm et al., 2016), which analyzed driverless parking and charging. These projects have in common that they focus on the technical implementation of the system and the regulatory implications. As a consequence, a limited number of vehicles were tested and hence, the interaction of the vehicles in regards to the services provided were not considered.

This leaves room for a more generic view on the AVP system and raises the question of implications for the operation of a corresponding car park, especially with regards to the scheduling of AVPS with a dynamic and stochastic arrival of new customers and a large number of service stations. For such applications, the Job-Shop Scheduling Problem (JSP) can be used to schedule services but provides unnecessary restrictions, such as a fixed order of the provision of services and a strict allocation of one service to one service station (Zhang et al., 2019). The Flexible Job-Shop Problem (FJSP) is an extension of the basic JSP, which allows services to be allocated to a subset of service stations but still requires a predetermined sequence of services (Ho and Tay, 2005). In this study, we provide a novel extension of the FJSP that allows an online operation while incorporating the requirements of an AVP system and evaluate the results both in regards to their quality of scheduling as well as run-time.

Our contribution is threefold. First, we extend the current AVP system with a generic view on AVPS while considering their constraints. The results help car park operators to quantify the benefit of integrating AVP systems with additional services. Second, we identify scheduling approaches for AVPS and show that the FJSP can be modified to address the needs of an AVP system, resulting in a novel online FJSP (OFJSP) extension. And third, we apply the modified OFJSP to a car park in a case study and identify its strengths and weaknesses compared to heuristic scheduling approaches under different environmental circumstances.

7.2. Related Work

AVP is a new concept and no technical standard has been established yet. In this chapter, we provide insights from literature on the state of the art of an AVP system setup, the available implementations and the potential for future extensions. We also introduce possible modeling and solving approaches for the JSP to outline the research gap of the OFJSP.

AVP The AVP system includes a drop-off and pick-up area, where the vehicles are handed over to the system or returned to their owner, respectively. From there, the system guides the vehicle to a nearby parking spot where it waits for the owner to return, combining both the search for a parking spot and the parking maneuver (Banzhaf et al., 2017). As the AVP is restricted to a controlled space, it is considered as one of the first use cases for autonomous driving, because vehicles can move without any danger to humans (Min and Choi, 2013; Leitner et al., 2020; Banzhaf et al., 2017). Besides an increased comfort for the vehicle owner, AVP also provides other benefits for today's mobility challenges, such as a decrease in parking area needed (Pedro M. dOrey, Jose Azevedo, Michel Ferreira, 2017) and a reduction of the distance driven to search for a parking spot, reducing corresponding carbon emissions (Azevedo et al., 2020).

Technical implementation There are different technical implementations of AVP being tested, which can be categorized depending on where the decisions of the system are made and who bears the legal and technical responsibilities (Banzhaf et al., 2017). First, there is purely vehicle based AVP. In this specification of the AVP system, the vehicle is equipped with all the sensors to navigate through the car park and determines by itself where to go. The second concept is a cooperative approach, where the vehicle and the infrastructure of the parking lot work together to allow for a safe operation. The sensors on the vehicle can be used to detect obstacles and to track the position of the vehicle, while a parking control system communicates parking space locations and provides driving path planning (Kang et al., 2017). The third and last approach is an AVP system that only relies on the infrastructure of the parking lot. In this scenario, the vehicle becomes a remote controlled car that receives instructions and follows them (Seonwook et al., 2019).

AVP Systems To ensure a reliable operation, there are tasks that need to be considered to create a working AVP system. The authors of (Banzhaf et al., 2017) define the three subsystems *Mapping*, *Perception* and *Communication*. Within the *Mapping* system, information on the design of the car park is provided, which helps finding a path to the desired destination. This data is used by the global path planning, which relies on known environmental information and is complemented by the local path planning, which considers uncertain environmental changes (Wang et al., 2014). In combination, this allows a collision free coordination within the car park and can be translated into an Multi-Agent Path Planning problem, which is NP-hard to compute (Yu and LaValle, 2013). The *Perception* subsystem collects all the data provided by different sensors in the AVP system and aggregates them to create a detailed representation of the AVP environment. The *Communication* system defines, both, the interaction of the vehicle with the infrastructure and between the user and the AVP system.

Extensions The subsystems described above allow an automated navigation through a car park and hence, are the foundation of any AVP system. In addition, there are several extensions to further utilize the advantages of AVP. One extension of AVP is to provide services while the vehicle is located at the car park. The combination of AVP and the possibility to charge an EV has the potential to provide utility gains to EV drivers and addresses two major challenges of electric mobility, which are long charging times and limited range (Timpner and Wolf, 2014). The authors of (Schwesinger et al., 2016) describe an AVP demonstrator where a VW e-Golf was modified for automated parking and charging using solely close-to-market sensors. Using a robotic arm, the charging session can start without any human interaction. In (Klemm et al., 2016), the authors demonstrate the efficient multi-story navigation of an electric smart vehicle. They identify AVP as a possibility to share one charging station between multiple EVs and employed an AVP system capable of parking and charging vehicles in a GPS denied environment (such as a parking garage).

These projects show that it is technically possible to provide services in AVP systems and they indicate that there is a demand from customers. Nevertheless, the projects are limited to one or just a few service providers. The question that remains is how a system with multiple service providers should be operated and especially, how vehicles need to be scheduled for individual services to successfully execute as many services as possible through the AVP system. In this study, we address this gap by developing a novel scheduling approach based on the FJSP.

Scheduling of Services Scheduling is a decision-making process with the aim of allocating resources to tasks over a given time period while optimizing one or more objectives (Pinedo, 2016). In the context of AVP, a task is a service requested by a customer, the resources are service stations and the objective is to handle as many services as possible within the constraints given by the dwell time of the customer.

There are multiple methods to create valid schedules, such as rule based heuristics that provide a satisfying result in a reasonable time or the JSP that aims to determine the optimal result for a given objective function. (Lin et al., 2012) define five core models of scheduling with the JSP being the fundamental model, where the objective is to minimize the makespan while considering the precedence and no-overlap constraint. The JSP is well established in the literature and several extensions are available, such as the Flow shop problem (FSP) with an identical sequence of tasks for every job (Soukhal et al., 2005), the Open-Shop Scheduling Problem (OSSP), where the operations of each job can be scheduled in any sequence (Anand and Panneerselvam, 2015) or the FJSP, where in addition to the variable sequence within a job, a task can be handled by a selection of machines (Ho and Tay, 2005). Further, there are various objectives such as minimizing the makespan (e.g. Kis et al. (2010)), minimizing earliness or tardiness (e.g. Grimes and Hebrard (2011)) or minimizing the sum of completion times of jobs (e.g. Anand and Panneerselvam (2015)).

The JSP is an NP-hard combinatorial problem (Zhang et al., 2019) and hence, does not scale well. Even small instances, such as the benchmark introduced by Fischer and Thompson in 1963 with 10 machines and 10 jobs, were a large challenge for 25 years (Błażewicz et al., 1996). Research has addressed this issue by providing insights on the run-time using different instances as well as different solvers. The authors of (Tamura et al., 2009) apply a SAT solver to the OSSP and find that 50% of the instances cannot be solved within one minute, with the largest scenario being 20 machines and 20 jobs. Even with a time limit of 3 hours, 2 of the instances analyzed could not be solved. In the study by Da Col and Teppan (2019), industrial size JSPs are compared in regards to their performance using different solvers. They find that their smallest instance, using 10 machines and 10 jobs, could be solved in around 2 hours, whereas the largest scenario with 1000 machines and 1000 jobs took 282 hours to solve. (Zhang et al., 2019) conclude that exact methods for the JSP are not suitable for large real world applications. In an AVP setup, the arrival rate of customers determines the available computing time, which can be below one minute (e.g. Abdel-Aal (2020); Klappenecker et al. (2014)). Extensions, such as the FJSP, are more complex than the JSP (Zhang et al., 2019) putting additional pressure on the time constraint of the AVP setup. An efficient approach is needed to address the trade-off between run-time and quality of results, while considering the constraint given by the online operation for the AVP scenario.

For such applications, constraint programming (CP) has gained a lot of attention in recent research. The structure of the JSP can easily be translated into an constraint satisfaction problem (Da Col and Teppan, 2019) and has the advantage that additional constraints can easily be integrated to address real world requirements (Beck et al., 2011). Such constraints could include additional costs for tardiness, for instance (Grimes and Hebrard, 2011). CP creates feasible solutions that are not necessarily optimal (Pinedo, 2016). It belongs to the artificial intelligence approaches, with the aim to effectively reduce the solution space (Zhang et al., 2019). The advantage of the CP approach is that it provides a feasible schedule quickly and improves the result over time.

7.3. Methodology

Integrating a platform for service providers in an AVP system and scheduling services of a car park is a novel approach and consequently, there is little insight from literature. To address this shortcoming, we describe the design of an AVP system with an integrated service infrastructure and we give examples for an implementation in a real world operation.

7.3.1. Service Subsystem

Building on the basic subsystems of AVP described in Chapter 7.2, we extend current literature with an additional *Services* subsystem. The main objective of the *Services* subsystem is to receive service requests from the customers and while considering the supply of service stations and their restrictions, to provide a schedule that incorporates which vehicle will receive which service at what service station and at what time. Given this process and the corresponding constraints, a service schedule has to be determined that satisfies as many service requests as possible.

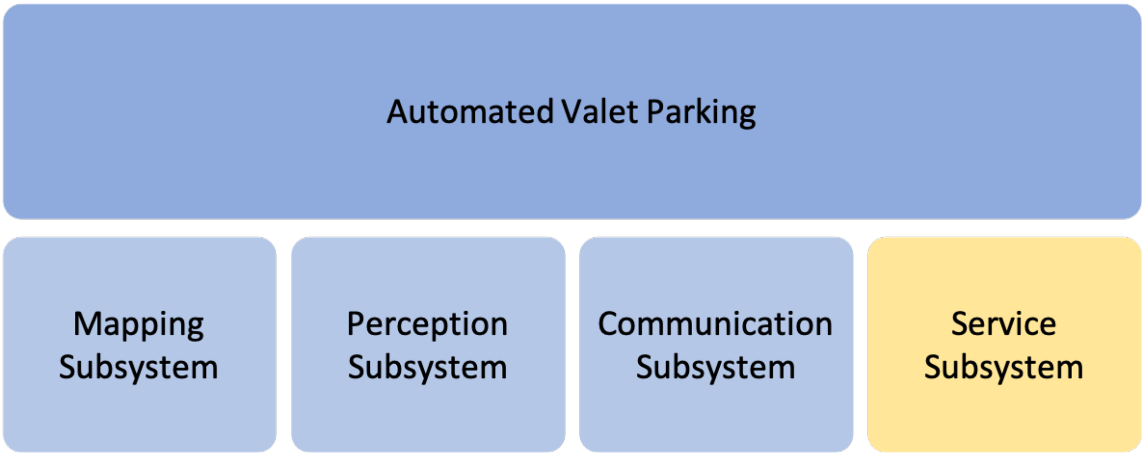

Figure 7.1.: AVP System and Subsystems

Definitions Within the AVP system, there are three components to consider, which are the customer, the AVPS and the service stations. A **Customer** is a person or a group arriving at the car park in one vehicle. Each customer has an individual arrival and departure time and is linked to a list of AVPS requests, which are ordered by priority. An **AVPS** describes a service provided by the AVP system and can be handled on a set of compatible and available service stations. Each AVPS is non-preemtive and can have individual properties, such as the amount of energy requested or the quality of a service, e.g. standard or detailed car wash, which are translated into a processing time for each service station. In this study, we focus on three AVPS types, which are charging, washing and loading a vehicle but any other service with a processing time that is known at the time of booking can be included. A **Service Station** provides AVPSs at a fixed location within the car park and is compatible with a subset of service types. Each service station is capable to handle one AVPS at a time. In the context of a car park, a service can both be linked to multiple service stations with divergent processing times or multiple services can be linked to one service station. In the first case, a charging service, for instance, can be supplied by a slow or fast charger. Even though the customer does not experience any difference when picking up the vehicle, the service time of the same request can differ. The second case describes, for example, a washing station that can provide different services, such as vacuuming or washing the vehicle.

Implementation The implementation of the *Services* subsystem is integrated in an infrastructure based AVP (see Chapter 7.2), where a central instance controls the movements of the vehicles. We use this implementation as we see the need for a central intelligence to schedule services in order to utilize the full potential of the system. We acknowledge that an implementation using a hybrid AVP can also provide good results and should be analyzed in future research.

The *Services* subsystem follows a straightforward process. While in operation, the subsystem receives service requests from customers and stores them for the dwell time of the vehicle. Once the state of the AVP system changes, for example, if a new vehicle arrives or a customer changes a service request, the *Services* subsystem collects information of the current state of the infrastructure and service providers and provides a new schedule. The schedule is then communicated to the AVP system and translated into commands for the remaining operation, such as a reallocation of a vehicle. The process is repeated as long as there are vehicles in the system. Note that the schedule has to be recalculated continuously.

7.3.2. Scheduling of Services

In order to define which AVPS will be handled when and on which service station, a scheduling approach is needed. Overall, the scheduling approach has to address three decisions: First, the machine allocation needs to be determined, which defines the exact machine that will handle a requested service. In an AVP system, there might be more than one service station capable of providing the same service (e.g. multiple charging stations) out of which the scheduling approach has to assign one to the service request. The second decision is the order in which the services of a single customer are handled. As the exact movements of the vehicle inside the AVP system are not visible to the customer, the system can choose the exact order as long as all services are provided upon departure. The third and last decision is the order in which services are handled on a single machine. All three decision are strongly connected with each other and hence, have to be addressed simultaneously.

7.3.3. Optimization Problem

There are multiple solutions and processes to create valid schedules that consider all three decisions, such as rule based heuristics. Another approach is to formulate the problem as a job-shop scheduling problem, which can provide an optimal solution, but belongs to the most difficult problems in combinatorial optimization (Liu et al., 2018). In this section, we focus on the JSP and introduce a novel extension to address the requirements of an online AVP operation with an AVPS integration. We select the JSP because the quality of the schedule directly translates into the number of successfully handled services, which benefits both the car park operator as well as the customers and hence even a modest improvement in the schedule can benefit both sides.

In the basic JSP, there is a set of n jobs $J = \{J_i\}_{1 \leq i \leq n}$, a set of m machines $M = \{M_k\}_{1 \leq k \leq m}$ and a set of operations $G_i = \{O_{i,j}\}_{1 \leq j \leq O(i)}$, where $O(i)$ defines the total number of operations of a job i. Each operation has a start time $s_{i,j}$ and a processing time $p_{i,j}$. The objective is to find a valid allocation of all operations to corresponding machines while minimizing the makespan, which describes the time between the start of the first and the end time of the last operation. The JSP is part of the class of combinatorial problems and is NP-hard, as the solution space increases exponentially (Zhang et al., 2019). The JSP can be applied in many different areas such as computer and manufacturing systems and hence, is one of the most studied and analyzed scheduling approaches (Da Col and Teppan, 2019). To allow the variable selection of one machine among equal machines, we use the Flexible Job-Shop Problem (FJSP), which is a variation of the JSP that allows jobs to be assigned to a set of compatible machines (Zhang et al., 2019). In the FJSP, $O_{i,j,k} \in \{0, 1\}$ denotes whether an operation $O_{i,j}$ is assigned to machine k. We follow the notations used in (Ho and Tay, 2005) and extend the basic FJSP with the requirements set of an AVP system. An overview over all parameters and decision variables is provided in Table 7.1.

The original FJSP and JSP are based on the same two constraints, which are the precedence and the no-overlap constraints. The first ensures that the start time $s_{i,j}$ of the operation $O_{i,j}$ is scheduled after the preceding operation is completed, hence, securing the predetermined order of operations. This constraint is important in the

Table 7.1.: Notation for Job-Shop-Problem - Input Parameters

Indices and parameters	
$J = \{J_i\}_{1 \leq i \leq n}$	Set of Jobs
$M = \{M_k\}_{1 \leq k \leq m}$	Set of Machines
$G = \{O_{i,j}\}_{1 \leq j \leq O(i)}$	Set of Operations
$O(i)$	Total number of Operations of Job i
$F(O_{i,j}) \subseteq M$	Compatible Machines for Operation$O_{i,j}$
$p_{i,j,k}$	Processing time of and operation [min] on machine k
a_i	Arrival time of job i
d_i	Departure time (Deadline) of job i
Decision variables	
$s_{i,j}$	Start of job i and operation j
$O_{i,j,k} \in \{0,1\}$	Allocation of Operation $O_{i,j}$ to machine k
Input variables	
$T_{i,j}$	Tardiness of operation $O_{i,j}$ [min]
$E_{i,j} \in \{0,1\}$	Indicates if $O_{i,j}$ is executed successfully
$B(M_k)$	Initial blocked time of Machine M_k
$B(J_i)$	Initial blocked time of Job J_i

context of production as certain production steps have to be completed in order to be able to perform the next part. In the context of AVP, this is negligible, as each service is independent. As a consequence, we remove the precedence constraint from our optimization problem. The latter constraint is used to make sure that at any time t, every machine is assigned at most one operation (Constraint 7.1). In addition, the constraint also ensures that at any time t, every job is assigned to not more than one machine.

$$s_{i,j} + p_{i,j,k} \geq s_{a,b} \tag{7.1a}$$

$$\text{or } s_{a,b} + p_{a,b,k} \geq s_{i,j} \tag{7.1b}$$

$$\forall (i,j),(a,b) \in G_i \text{ where } (i,j) \neq (a,b)$$

In the FJSP, the scheduler is free to assign an operation $O_{i,j}$ to any machine within a set of compatible machines $F(O_{i,j}) \subseteq M$. To ensure that every operation is allocated to exactly one machine, we add Constraint 7.2a.

$$\sum_k O_{i,j,k} = 1 \quad \forall k \in F(O_{i,j}) \tag{7.2a}$$

Every vehicle in the AVP system is parked for a limited time only, which is why a deadline for the completion of all services of a job i is needed. We assume that the departure time d_i is known in advance. There are several examples of deadlines integrated in the JSP and FJSP (e.g. Balas et al. (1998, 2008)) where either the sum of delayed services (e.g. Bahroun et al. (2018)) or the aggregated tardiness of services are minimized (e.g. Zhu and Heady (2000)). They share the characteristic that every operation needs to be scheduled regardless of the delay. This is not the case in an AVP system as there is no possibility to provide a service after the customer has left and customers cannot be forced to stay until all services are provided. To account for this requirement, we track both the tardiness $T_{i,j}$ (Equation 7.3a) and if a service is executed or not with the binary variable $E_{i,j}$ (Equation 7.3b).

$$T_{i,j} = c_i - d_i \tag{7.3a}$$

$$E_{i,j} = \begin{cases} 1, & T_{i,j} > 0 \\ 0, & else \end{cases} \tag{7.3b}$$

With these two variables, we are able to identify all services that can be scheduled within the dwell time of the vehicle.

One main challenge of an AVP system is that there is no perfect foresight regarding the arrival of vehicles and requested services. We assume that vehicles arrive randomly at the AVP system and that there is no foresight in regards to neither the arrival nor the dwell time of future customers or their requested services. As a consequence, the optimization has to be updated every time new information becomes available to the system. An update could be the arrival of a new customer or if additional services are booked at a later point in time. To address this requirement, we include two constraints to incorporate the current state of the AVP system into the optimization problem. As the original JSP assumes that information on every machine and job is known at $t = 0$, we extend this with two blockage constraints. As services are non-preemptive, services can be currently assigned to a machine due to an earlier optimization at the time when new information becomes available to the system but can then not be interrupted or modified until completion. In this case, the service and the corresponding machine are not available at $t = 0$ of the consecutive optimization and need to be blocked. This is done in Constraint 7.4a for the machine and Constraint 7.4b for the service, respectively. The function $B(*)$ returns the time until the machine or service are blocked, where $t = 0$ is the time period when new information becomes available.

$$s_{i,j} \geq B(M_k) \quad \forall O_{i,j,k} = 1 \tag{7.4a}$$

$$s_{i,j} \geq B(J_i) \quad \forall J_i \in J \tag{7.4b}$$

Given these constraints, the main objective of the optimization problem is to successfully schedule as many services as possible, i.e. to maximize the number of executed services. The corresponding objective is defined in the objective Function 7.5a. The contribution of this objective is twofold. First, it provides information on how many services can be scheduled within the dwell time of each individual customer and hence, allows a comparison between booked and scheduled services. Second, due to the variable $E_{i,j}$, the objective also provides the subset of services that are feasible within the constraints. This is important information due to the stochastic nature of the input data. As there is no information on future arrivals, the optimization problem cannot anticipate future demand and, therefore, finds an optimal solution given the currently provided information. Even if the optimization problem discovers the global minimum of services not scheduled, this does not necessarily lead to an optimal schedule over the entire time of operation due to changing information. For example, in a scenario with only one charging station, once the first EV arrives, the optimization problem can schedule the charging session as late as possible. This would lead to an optimal solution as all services are successfully scheduled. Once the second EV arrives, this could lead to a problem as the charging station is in use and the vehicle schedule does not possess any flexibility to postpone the charging session. As a consequence, the second EV might not be able to charge, which again represents an optimal solution within the optimization problem. However, globally this does not describe an optimal solution. To address this issue, we use an iterative approach which extends the original formulation of the FJSP. Once the subset of feasible services is determined, we repeat the optimization on the subset using a second objective function. This objective function minimizes the aggregated completion time of all feasible services and is defined as objective function 7.5b. The objective function ensures that every service is scheduled as early as possible, therefore, providing more flexibility to future optimization problems once new information is provided to the system.

$$max \sum_{i \in J, j \in G_i} E_{i,j} \tag{7.5a}$$

$$\begin{aligned} min \sum_{i \in J, j \in G_i} s_{i,j} + p_{i,j,k} \\ where \quad E_{i,j} = 1, O_{i,j,k} = 1 \end{aligned} \tag{7.5b}$$

The combination of the additional constraints and the iterative solution approach over two steps creates a novel online flexible Job-Shop problem and is analyzed in further detail in the following sections. A complete overview of the properties of the OFJSP as well as a differentiation against the JSP and FJSP are provided in Table 7.2.

7.3.4. Implementation and run-time

The rationale of the iterative approach is grounded in the performance from both, a quality as well as a run-time perspective. The first objective ensures the main goal,

Table 7.2.: Properties of the Optimization Problems

Property	JSP	FJSP	OFJSP
no precedence	×	×	✓
no overlap	✓	✓	✓
blocked services	×	×	✓
blocked machines	×	×	✓
tardiness	×	×	✓
flexible machine allocation	×	✓	✓
online	×	×	✓

which is to provide as many services as possible. The second objective increases the flexibility in future optimizations. The optimization problems are interconnected and the decisions of a preceding optimization impact the initial situation of the consecutive optimization. Besides the impact on the quality of the overall operation of the AVP system, the iterative approach also has a positive impact on run-time. Due to the online characteristics of the AVP use case, there is a need to provide a decision in reasonable time as during the time spent optimizing, no new allocations can be communicated to the vehicles. The optimization should therefore be completed before the next arrival. Otherwise, it will be stuck in a loop of calculations without providing a viable schedule. With our iterative approach, we contribute to this issue as we split the decision into determining the feasible services and determining a time efficient schedule. Whereas the former is a less complex decision, the latter can require a significant time to compute. By reducing the number of services after the first optimization, we ensure a faster computing time in the second.

Besides the design of the optimization problem, the choice of the scheduling algorithm and the implementation also have a large impact on the overall performance and the possibility of a real-time online operation of an AVP system.

The research on the run-time of the JSP and FJSP shows that in order to be used in an AVP system, optimality might not be achievable. As a consequence, a scheduling algorithm is needed that provides a valid schedule within a reasonable time, even if the result does not represent the global optimum. For such applications, constraint programming (CP) has gained a lot of attention in recent research. The advantage of the CP approach is that it provides a feasible schedule quickly and improves the result over time. A schedule is feasible if it complies with every constraint of the

OFJSP, but might not be optimal in regards to the objective functions. For the AVP system, this means that a time limit can be used to provide a faster response from the scheduling approach and to ensure the successful operation of the system. To implement the CP approach in the AVP system, we use the open source OR tools, as they have proven to be suitable in large real world use cases (Da Col and Teppan, 2019).

7.3.5. Benchmarks

As the online optimization with constraint programming of the OFJSP cannot guarantee an optimal solution, both, overall and on each individual optimization, we use benchmarks to assess the quality of the solution. These benchmarks are two heuristics (First-Come-First-Served and Random) based on simple rules to schedule services and two technical benchmarks to assess the quality of the AVP system. For the lower bound of the AVP, we calculate the scenario where no automation is implemented to represent current parking lots where vehicles do not move after being parked. For the upper bound, we implement an optimization with complete information. Here, all arrivals, departures and service requests are known in advance. The four benchmarks are further described in the following.

FCFS The First-Come-First-Served (FCFS) heuristic simulates the current behavior at car parks. Vehicles arriving first have the possibility to choose any parking lot, charging station or other service station that is currently available. It therefore is a close representation of current service allocation in parking lots with the extension that vehicles can (re-)park autonomously. The strength of the FCFS heuristic is that it creates dense schedules, as arriving vehicles are instantly scheduled if possible or if service stations are occupied, the first available time slot is booked. This approach has been proven to provide good results in smart charging scenarios without information on future trips (Flath et al., 2012) and is therefore a promising scheduling algorithm. The FCFS heuristic follows a similar objective as the second objective function of the OFJSP formulation, which is to schedule services as fast as possible and hence, to provide as much flexibility to the following iterations as possible. In our implementation of the FCFS heuristic, the algorithm first determines the set of service stations with the earliest possible start time and, in a second step, chooses the station with the shortest completion time. This decision is relevant for services, where multiple machines are capable of providing the service at different speed, such as charging stations where slow and fast charging stations can supply the energy needed.

Random The Random heuristic is used as a lower benchmark for the scheduling algorithms and addresses the question of whether any prioritization or optimization is needed. In this scheduling approach, a random possible start for the service is selected, where every time $t \in T$ has the same probability to be selected as long as the service is completed before the departure of the vehicle and, both, the vehicles and service stations do not have overlapping services. The random approach does not prioritize any service station.

No AVP While the two heuristics are used to benchmark the quality of the OFJSP solution, we use the *no-avp* benchmark as a lower bound for the AVP system overall. It quantifies whether an AVP system has any value at all compared to today's parking reality. Without an AVP system, the customer performs the top priority service, possibly among a set of services, if the corresponding service station is available. If a set of possible service stations is available, the customer chooses the station with the shortest service time. The vehicle is then parked at the service station and stays parked until departure. In case no service station is available at arrival, the customer parks at a regular parking lot. Note that the customer cannot satisfy more than one service with this approach.

Complete Information Poor scheduling decisions are not necessarily the reason for unfulfilled service requests. There are several factors that limit the number of completed services, for instance, an overload of the infrastructure. In a scenario where the number of requested services exceeds the overall capacity on site, no scheduling approach is capable to allocate all requested services successfully. To distinguish unfulfilled services caused by infrastructure overload from poor scheduling decisions, we implement the *complete information* benchmark. For this benchmark, we apply a variation of the OFJSP described in Chapter 7.3.3. We limit the optimization to the first objective function as no online optimization is necessary and use Constraint 7.4b to include the time until arrival, during which vehicles cannot receive any services. Even though the optimization is limited to the first constraint, not all scenarios can be computed in reasonable time. We therefore impose a time constraint of four hours and use the solution found at that time. A detailed analysis of the run-time including a justification for the four hours restriction is provided in Chapter 7.5.2.

Using these approaches, we can calculate a lower benchmark with *no-avp* and an upper benchmark with *complete information* to asses the quality of the scheduling approaches. In addition, using the two heuristics, we can evaluate if and in which scenarios, the JSP can improve online operation beyond computationally less expensive solutions.

7.4. Case Study

In order to assess the operation of the AVP system as a whole, we implement a simulation that resembles the movement of individual vehicles in a car park represented by a network graph. This allows a close representation of the use case AVP and incorporates the unique challenges and requirements of automated vehicle coordination as well as the interactions between vehicles and the infrastructure.

7.4.1. Simulation

Setup The core of the simulation is based on *SimPy*, a process based discrete-event simulation framework implemented in *Python* (Team SimPy, 2021). Here, both, the vehicle and the service subsystem have an individual process for operation.

The vehicle is generated at the beginning of the simulation and equipped with an arrival and departure time as well as the set of services. Once the simulation period reaches the arrival time, the vehicles registers at the service subsystem and communicates the requested services. The vehicle then awaits a command from the service subsystem. Once the command is received, the vehicles executes the command and returns to the state where it is waiting for new commands. As soon as the departure time is reached, the vehicles departs from the parking lot and no further commands can be executed. Possible commands for a vehicle are parking in a parking lot or visiting a service station.

The service subsystem is a unique process for each car park and is responsible for scheduling the requested services and for communicating the schedule to the mapping subsystem to allow for the navigation of vehicles inside the AVP system. Once created, the service subsystem waits for service requests. Next to the services provided by individual service stations such as charging, parking is also considered a service and every parking lot is considered a unique service station for parking. However, we do not consider parking services in the evaluation hereafter as parking service requests can always be fulfilled. For every service registered, the service subsystem then calls the scheduling service, which, depending on the scenario, determines the start and service station of the service using one of the decision heuristics or the OFJSP. Every execution of the OFJSP is limited to 15 seconds for each objective function as we assume an average arrival rate of four vehicles per minute. To reduce the waiting time before another service, the service subsystem assigns the closest parking lot to the next service station to a vehicle to keep the arrival as short as possible. Once the service is scheduled, the service subsystem informs the mapping subsystem to calculate the path to the service station, which sends a command to all the vehicles with an updated path. To do so, we use the Dijkstra algorithm to calculate the shortest path, which has been shown to provide good results in reasonable time in different AVP applications (e.g. Loper et al. (2013)).

The process and interaction of the vehicles and the *Service* and *Mapping* subsystems are illustrated in Figure 7.2.

Scenario Setup

To define the scenarios, we differentiate between parameters that specify the infrastructure at the car park and parameters describing the user behavior of customers.

Infrastructure Every car park is designed differently and there is no standard layout available. This has lead to the development of multiple techniques to find the optimal layout for a particular parking lot (Young, 1988). Nevertheless, to provide generalizable findings for AVP systems and to reduce the impact of specific car park designs, we base our parking lot on a design element found in parking lots all over

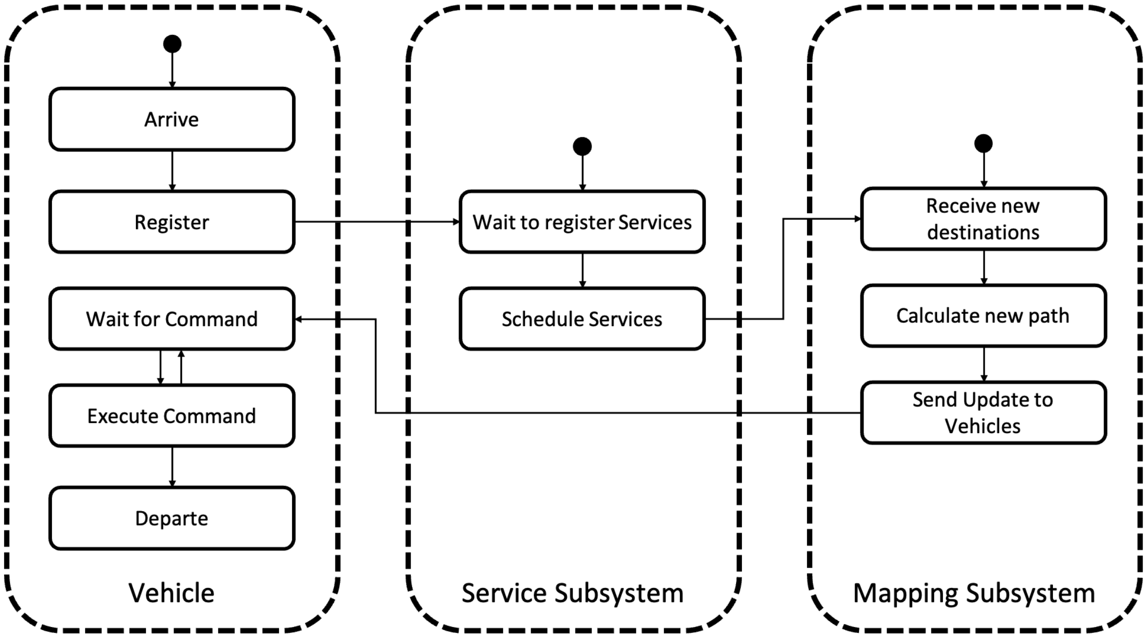

Figure 7.2.: Interaction of a vehicle with the AVP system

the world where vehicles are parked in islands of two, where each vehicle has its own access to the driveway. We scale this design to incorporated 10 bays with 10 vehicles parked in each row. An illustration of the car park is shown in Figure 7.3, where the grey nodes represent driveways and the green nodes represent parking lots. In total, this leads to a car park with 200 parking lots. The entrance is on the lower left (brown node) and the exit on the upper left (blue node).

We position the charging and washing stations in the outer left bay, where the charging stations are positioned left of the driveway and the washing station on the right. The number of service stations is varied per scenario. In scenarios with more than 10 service stations, we repeat the same allocation one bay to the right until all service stations are located in the car park. As some service stations can be in a remote location, we positioned the loading area at the bay on the right side. This way, we can analyze the impact on the mobility within the AVP system.

In the basic setup, we include 12 charging stations out of which 4 are fast chargers (50kW) and 8 regular chargers (11kW). In addition, we add 10 service stations for washing vehicles and 4 loading stations. Whereas the charging stations provide one service with different speeds, the washing and loading stations can provide services of different quality. We differentiate between a small and a large service, where

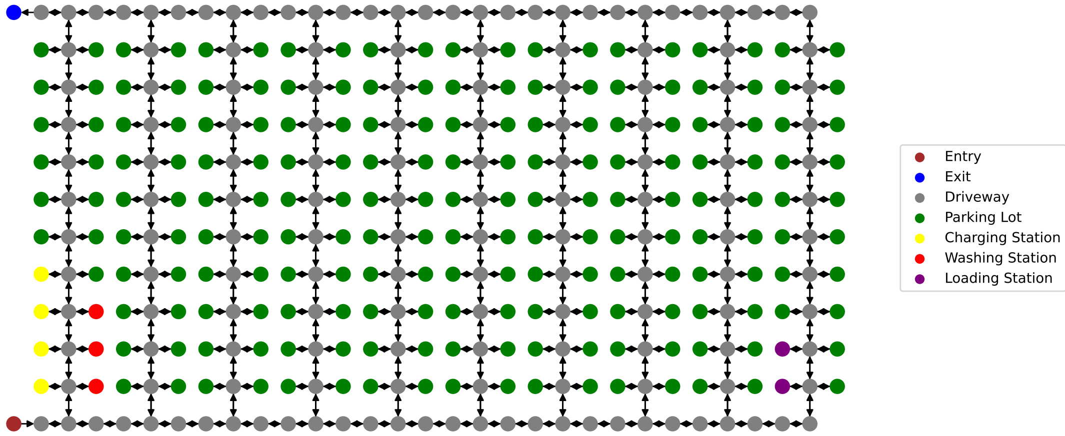

Figure 7.3.: Exemplary Car Park Layout with 200 parking lots

the washing takes 15 or 30 minutes and the loading 5 or 10 minutes, respectively. Overall, we acknowledge that the services provided in this simulation are fictional and could be replaced with others. Nevertheless, the combination of different services with variable processing times is an important requirement in an AVP system and hence, is included in the case study.

User Behavior As there are no AVP systems providing services in operation today, there is no documented data on the demand for AVPS. To address this, we base our simulation on a medium size car park and use scenarios to evaluate the impact of different utilization rates. If not explicitly changed, we simulate 1000 vehicles with an arrival rate of 60 vehicles per hour. On average, each vehicles has a dwell time of 90 minutes with a minimum of 60 and a maximum of 120 minutes. The dwell time follows a uniform distribution. We assume, that there is a 30% chance of a customer requesting each service with a 50% chance for the small and large service, respectively. Each charging request is randomly drawn from a uniform distribution in a 4kWh interval around the mean of 13.3kWh. (Electrive.net, 2020).

Scenarios

The utilization of car parks differs and varies for a single car park between or within a day. This raises the question of how the scheduling approaches can handle different utilization rates and if there are advantages for some approaches given certain scenarios. To address this, we implement three sets of scenarios that vary the flexibility provided to the system as well as the utilization of the system from a car park, service station and customer perspective.

Arrival Rate Car Parks can be exposed to an on- and off-peak utilization, where at certain times, a high number of vehicles enters the car park. To analyze how the different scheduling approaches handle these situations, we vary the average number of vehicles within the system. To do this, we use Little's Law to determine the average number of vehicles L in the car park in a steady state. For a given arrival rate and dwell time, Little's Law provides the average number of vehicles within the system. The exact formulation is given in Formula 7.6a. The capacity utilization C^{Util} is then calculated as the ratio of the number of vehicles L and the total number of parking lots in the car park $\mid PL \mid$. With a constant waiting time W inside the AVP system, we increase the average number of vehicles arriving per time unit λ to represent a utilization of 10% to 100% of the parking spaces.

$$L = \lambda \cdot W \tag{7.6a}$$

$$C^{Util} = \frac{L}{\mid PL \mid} \tag{7.6b}$$

Between the scenarios, the customers have identical distributions of needs and dwell times. The only parameter adapted is the time between the arrivals of customers. Overall, we analyze 9 individual scenarios $P_{C^{Util}}$ with $C^{Util} \in [10\%, 20\%, ..., 100\%]$ where C^{Util} describes the share of parking spaces utilized in a steady state.

Flexibility of Customers With an increasing acceptance for AVPS, the demand of customers will likely increase leading to more services requested per customer. As we cannot assume that the dwell time will increase likewise, the time flexibility of each customer within the AVP system decreases. Time flexibility in the context of this simulation describes the ratio of the aggregated processing time of all services and the dwell time of a customer and is a relevant factor for example to charge EVs (Huber et al., 2020). For AVPS with heterogeneous processing times for different machines, the machine with the minimal process time is selected, for example, if a fast or slow charger can perform the service, fast charging is selected.

$$f_i = 1 - \frac{\sum_{j=1}^{O(i)} \min_{k \in F(O_{i,j})} p_{i,j,k}}{d_i - a_i} \tag{7.7a}$$

$$f^{avg} = \frac{\sum_{i=1}^{n} f_i}{n} \tag{7.7b}$$

By decreasing the average flexibility from 80% to 0%, we provide insights on how the scheduling approaches cope with an increasing number of services requested by customers up to the point where the infrastructure is not sufficient to handle every request. In total, this leads to 9 individual scenarios $F_{f^{avg}}$ where $f^{avg} \in [80\%, 70\%, ..., 0\%]$ describes the flexibility of an average customer (Constraint 7.7b).

Utilization of Service Stations Due to technical or financial limitations, it is possible that the number of service stations cannot be increased to provide adequate supply for the customers. Within these scenarios, we evaluate how the different scheduling approaches cope with different utilization rates of the service stations by decreasing the number of service providers for a constant demand. The utilization of a service station is determined by the aggregated demand of services in minutes divided by the maximum supply the service station can provide during a time period.

$$u_s = \frac{\sum_{1=i}^{n} \sum_{1=j}^{O(i)} \sum_{F(s)} p_{i,j,m}}{|F(s)| \cdot t_{max}} \tag{7.8a}$$

In total, we evaluate 10 utilization rates U_{u_s} where $u_s \in [10\%, 20\%, ..., 100\%]$ describes the utilization of all different service stations. An overview of all scenarios and the parameters used is provided in Table 7.3.

Table 7.3.: Parameters of all Scenarios

Scenario	Infrastructure				User Behavior			
	Slow Charging	Fast Charging	Washing Station	Loading Station	Arrival Rate [veh/h]	Prob. Charging [%]	Prob. Washing [%]	Prob. Loading [%]
P_{10}	12	4	10	4	20	30	30	30
P_{20}	12	4	10	4	40	30	30	30
P_{30}	12	4	10	4	60	30	30	30
P_{40}	12	4	10	4	80	30	30	30
P_{50}	12	4	10	4	100	30	30	30
P_{60}	12	4	10	4	120	30	30	30
P_{70}	12	4	10	4	140	30	30	30
P_{80}	12	4	10	4	160	30	30	30
P_{90}	12	4	10	4	180	30	30	30
P_{100}	12	4	10	4	200	30	30	30
U_{10}	40	25	50	20	60	30	30	30
U_{20}	30	10	30	10	60	30	30	30
U_{30}	40	4	20	7	60	30	30	30
U_{40}	20	4	15	5	60	30	30	30
U_{50}	14	4	12	4	60	30	30	30
U_{60}	10	4	11	3	60	30	30	30
U_{70}	10	3	10	3	60	30	30	30
U_{80}	7	3	9	3	60	30	30	30
U_{90}	5	3	8	2	60	30	30	30
U_{100}	4	3	7	2	60	30	30	30
F_{80}	12	4	10	4	60	18	19	19
F_{70}	12	4	10	4	60	27	27	27
F_{60}	12	4	10	4	60	36	36	36
F_{50}	12	4	10	4	60	45	45	45
F_{40}	12	4	10	4	60	54	54	54
F_{30}	12	4	10	4	60	63	63	63
F_{20}	12	4	10	4	60	72	72	72
F_{10}	12	4	10	4	60	81	81	81
F_{0}	12	4	10	4	60	90	90	90

7.5. Results

The results presented in this section are calculated on Debian Virtual Machines with 1 vCPU Core and 2GB RAM. This setup allows an independent simulation of each scenario without any interference in the run-time. The single CPU setup provides enough computing power as the CP algorithm can only utilize a single CPU for each optimization instance. Overall, the results are based on 10 independent runs per scenario.

7.5.1. Scenarios

In the three sets of scenarios addressed in this study, we compare the impact of increasing arrivals, decreasing flexibility of customers and increasing utilization of the service providers. The results of each scenario including the *no-avp* benchmark, the random and FCFS heuristic and the OFJSP without and with foresight are presented in Figure 7.4, 7.7 and 7.8. Each figure is split into two subfigures, where the first illustrates the average number of successful services for each scenario and scheduling approach. The data for complete information is split into scenarios where every run provided an optimal solution (continuous line) and scenarios where at least one run was feasible (dotted line) within the 4 hour time limit. In order to highlight the performance of the OFJSP in comparison to the FCFS, the second subfigures shows the absolute and relative difference between the two.

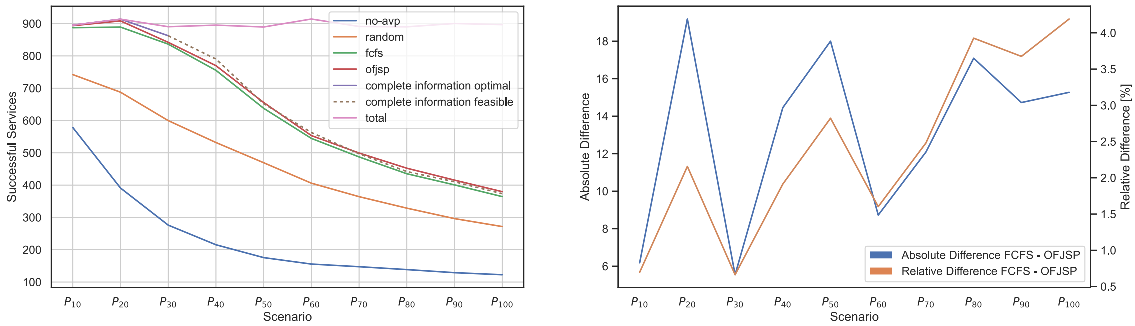

Figure 7.4.: Results of scenarios $P_{C^{Util}}$ with $C^{Util} \in [10\%, 20\%, ..., 100\%]$

Arrival Rate In the scenarios P_x with $x \in [10\%, 20\%, ..., 100\%]$, the average utilization of parking lots in the car park is raised by increasing the arrival rate of customers. As expected, the results show that with an increasing arrival rate, the absolute number of AVPS that are scheduled successfully decreases for all scheduling approaches. The worst performance is the *no-avp* benchmark with 64.6% of AVPS successfully scheduled in scenario P_{10} and around 13.7% in scenario P_{100}. This can be explained with the scheduling mechanism. In P_{10}, the utilization is very low. The service provider can handle every AVPS the customer requests, but only the highest priority AVPS of the requested AVPS is performed as vehicles are not relocated after the service is completed. With the user behavior in this scenario, around 600 customers have at least one AVPS request, which is served by the *no-avp* scheduling approach. With an increase in arrival rate, the service stations are more overcrowded, leading to a steep decrease in successful services as service stations are still blocked when new potential customers arrive. The same trend can be seen in the other scheduling approaches, but with a slower decline. The random heuristic provides better results than the *no-avp* approach, but lacks behind the FCFS and OFJSP approaches. With the random heuristic, vehicles can be relocated by the AVP system and hence more than one AVPS per customer can be scheduled. Nevertheless, due to the random nature of the scheduling approach, gaps occur between the services, leading to time intervals where the service providers do not handle customers, even though there are still open requests. The reason for this are the non-preemtive AVPS. As some gaps between services are shorter than the shortest AVP, there is no possibility to utilize the gap.

Figure 7.5.: Gantt Diagram of a schedule based on the Random heuristic

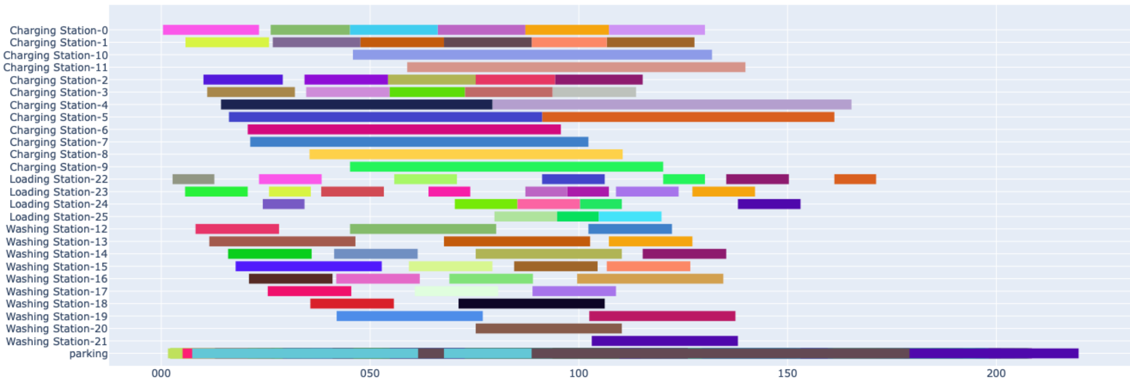

Figure 7.6.: Gantt Diagram of a schedule based on the FCFS heuristic

This is illustrated in Figure 7.5 and 7.6, where an examplary Gantt diagram of a schedule using the FCFS and the random heuristic are illustrated using 100 vehicles. The figures show that the resulting schedule of the FCFS heuristic creates a "dense" schedule without gaps between services if possible. This allows for a better utilization of the service stations and results in more services handled, overall. As a consequence, the FCFS heuristic provides good results when compared to the random heuristic. It also often performs similarly well as the OFJSP approach.

Figure 7.4 shows that the FCFS heuristic does not drop in performance as fast as the *no-avp* approach and is capable to schedule almost every service up to a utilization of 30%. It then follows an almost linear decrease in number of successfully scheduled services. Compared to the upper benchmark, the optimization with complete information, the FCFS heuristic does not provide the optimal result and further improvements are possible. The OFJSP approach, in comparison, provides the best results of all scheduling algorithms. Nevertheless, the difference to the FCFS heuristic is small in a range of 5.5 to 19.2 AVPS or 0.6% to 4.2%, respectively. The OFJSP is capable of utilizing the flexibility of the customers and rearranges service requests to maximize the number of successfully scheduled services. The results show that the schedules created provide close to optimal results. In addition, Figure 7.4 shows that the relative difference to the FCFS heuristic increases with an increasing arrival rate. With more vehicles in the car park, the OFJSP has more potential to prioritize single services to create an optimal schedule, whereas the FCFS does not rearrange customers over time.

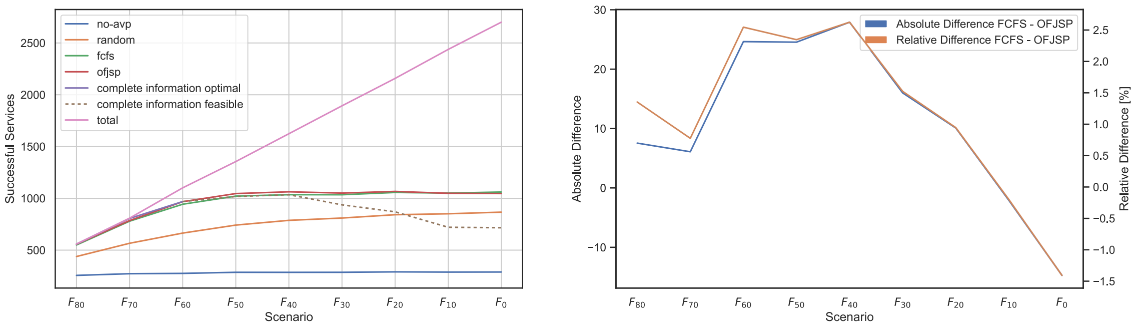

Figure 7.7.: Results of scenarios $F_{f^{avg}}$ where $f^{avg} \in [80\%, 70\%, ..., 0\%]$

Flexibility of Customers In the scenarios $F_{f^{avg}}$ with $f^{avg} \in [80\%, 70\%, ..., 0\%]$, we increase the service requests of customers, which results in a higher total number of services requested as well as less flexibility provided by each customer. Figure 7.7 shows that the total number of AVPS increases linearly whereas the successfully scheduled services in the *no-avp* approach stay the same. This is caused by the fact that for each customer, at most one service can be scheduled as described before. Using the random heuristic on the other hand, the AVP system utilizes the possibility to relocate vehicles and hence the number of successfully scheduled AVPS increases. Due to the capacity limitations of the service stations, the benefit of additional AVPS requests decreases and the heuristic reaches a plateau at around 800 successful services. As a result of the gaps between services, the service providers cannot be fully utilized and idle time occurs. When looking at the FCFS heuristic and the OFJSP without foresight, the results can be separated into three clusters. The first cluster covers scenario F_{80} and F_{70}. Here the flexibility provided by the customer is so broad that both approaches provide a close to optimal solution. In theses scenarios, the service stations are underutilized and hence, even a simple heuristic such as the FCFS approach provides optimal results. This changes in the second cluster covering scenarios F_{60} to F_{20}. Within these scenarios, the service providers have the potential to supply more services and it is the scheduling algorithms task to find the optimal allocation. Here, the OFJSP is capable to exploit the flexibility of customers and creates a schedule that is up to 2.5% or 25 AVPS superior to the FCFS heuristic. In the third cluster covering F_{10} and F_0, this changes as more and more service requests cannot be handled by the infrastructure and remain in the queue to be scheduled. Whereas in theory, the OFJSP should expand its lead over the FCFS heuristic, the opposite can be observed. Within the scenarios with the lowest flexibility of customers, the OFJSP under-performs compared to the FCFS heuristic. This can be traced back to the run-time limitations of the OFJSP as mentioned in Chapter 7.3.3, which is further analyzed in Chapter 7.5.2. Within the time limit of 15 seconds and with an increasing number of service requests, the CP approach does not have enough time to improve the schedule sufficiently, leading to sub-optimal results even below the performance of the FCFS heuristic.

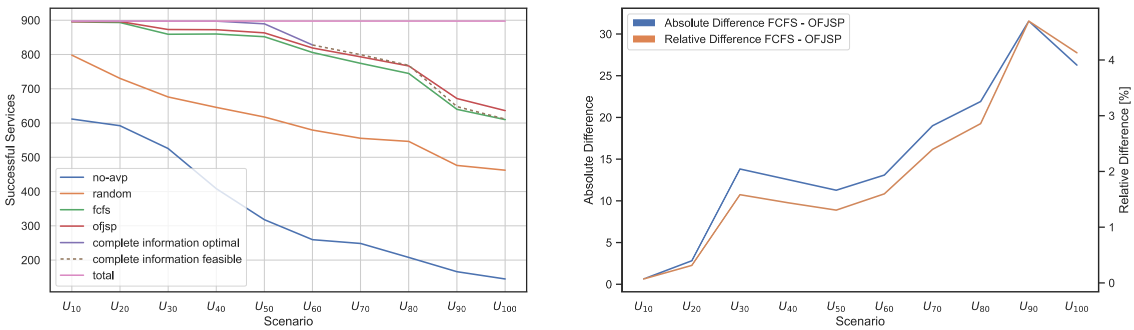

Figure 7.8.: Results of scenarios U_{u_s} with $u_s \in [10\%, 20\%, ..., 100\%]$

Utilization of Service Stations In the third set of scenarios U_{u_s} with $u_s \in [10\%, 20\%, ..., 100\%]$, we decrease the total number of service stations and hence, their flexibility. The results of the *no-avp* benchmark and random heuristic follow a similar trend as in the previous scenarios. Whereas the *no-avp* benchmark provides the worst results the random heuristic performs in between the FCFS heuristic and the *no-avp* benchmark and decreases with the reduction of service stations. The FCFS heuristic (and OFJSP without foresight) provide an optimal result in the first two scenarios U_{10} and U_{20}. Here, the large number of service stations is capable of handling all service requests and the resulting flexibility ensures that every customer request is scheduled. Whereas the OFJSP with foresight illustrates that up to scenario U_{50}, the infrastructure is capable to handle almost every service, the FCFS heuristic and OFJSP without foresight fail to schedule several services starting from scenario U_{30}. This trend continues with increasing utilization of service stations, but the magnitude to which the two approaches are impacted differs. As illustrated in Figure 7.8, the gap increases with a maximum of up to a total of 30 AVPS or 4.8% respectively, in favour of the OFJSP. This can be explained by looking at the input data of the simulation. In this set of scenarios, the number of customers and thus, the requested AVPS always enter the system at the same rate, but the number of service stations decreases. As a consequence, two factors impact the quality of the OFJSP. On one side, the number of services in the queue increases, which leads to an increase in complexity as shown in the previous paragraph. On the other side, the reduction in service stations decreases the complexity of the optimization problem. In addition, our iterative approach helps to reduce the number of services even further, as services that are technically not feasible are excluded from the second iteration. In total, this trade-off works in favor of the OFJSP and the number of additional AVPS scheduled in comparison to the FCFS heuristic increases.

7.5.2. Run-time

The described results show that the number of customers (jobs) and AVPSs impact the results and that different scheduling approaches are impacted differently. In this subsection, we address the issues associated with the scalability of the OFJSP and whether the approach is able to identify an optimal solution. Within each scenario, the OFJSP approach is computed several times as vehicles arrive at the car park and request AVPSs. In Figure 7.9, we show the share of OFJSP instances with optimal and feasible results for the scenarios P_x within one simulation run. The distribution illustrates that the OFJSP is able to compute the optimal result only in the scenarios with a long inter-arrival time. For scenarios P_{10} and P_{20}, more than 99% of optimization instances are optimal as only a few vehicles are inside the car park and the utilization of the service stations is low. This changes when vehicles are arriving more frequently. As a consequence, only a fraction of OFJSP instances find optimal solutions. These are the instances at the beginning of the simulation where the number of customers is low. As the car park utilization increases, the results become "feasible" and no conclusion on the quality of the result is possible.

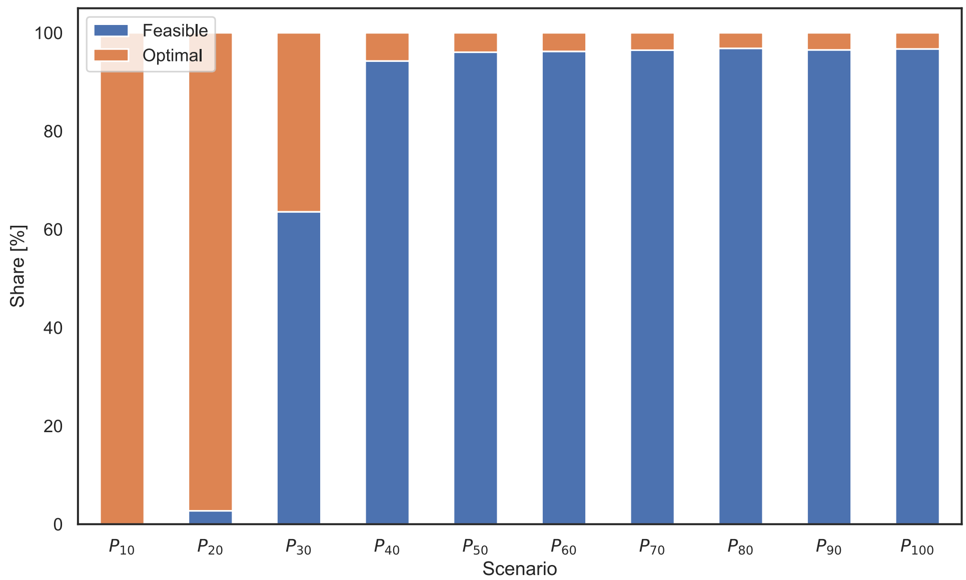

Figure 7.9.: Quality of results

To illustrate this in further detail, we focus on scenario P_{50} as a representative for a balanced number of customers without extreme under or over utilization of the service stations and analyze both the quality of the results as well as the improvements over time.

Quality of Results Figure 7.10 presents a histogram of the number of customers (jobs) handled within each optimization instance. With an average of 45 and a maximum of 71, the number of jobs is far above the benchmarks described in the

JSP literature and hence explains why the OFJSP cannot find an optimal solution within the 15 seconds time limit. Especially the instances with a high number of jobs give an indication why the FCFS heuristic and the OFJSP perform similarly in scenarios with a high utilization of the car park. For the operation of a car park using AVP technology, this implies that if the number of customers reaches a threshold, the benefits of the OFJSP decrease and the OFJSP can even underperform in comparison to FCFS as shown in scenario F_0. In scenario P_{50}, this threshold is at a maximum of 11 jobs in the queue, where the objectives of both stages of the OFJSP reach an optimal result. After 63 jobs in the queue, even the the first objective no longer reaches an optimal value. These thresholds illustrate the challenge of the NP-hard OFJSP problem as it does not scale well with an increasing number of customers.

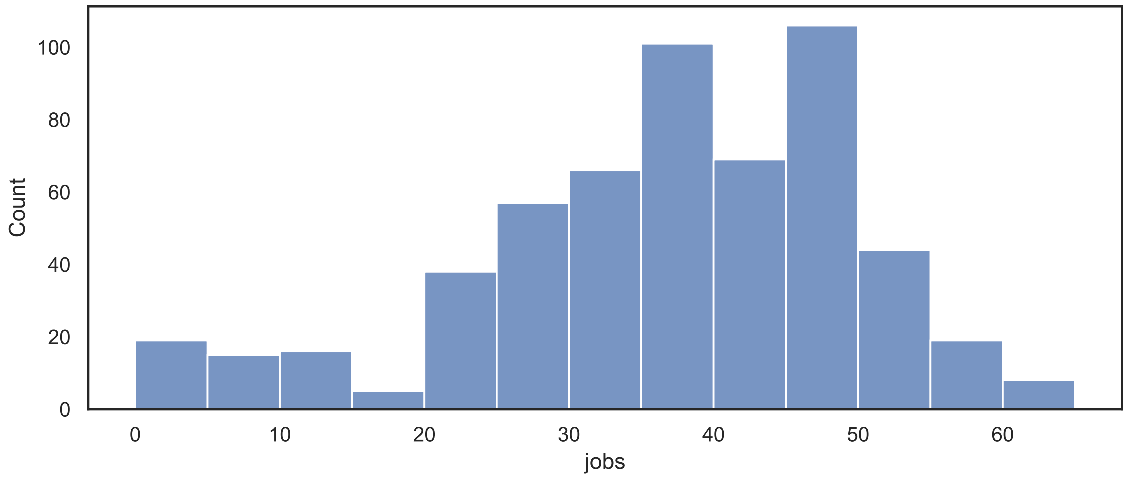

Figure 7.10.: Distribution Job Shop Instances

Impact of time The CP approach described in this study creates feasible schedules and improves them over time. This is illustrated in Figure 7.11, where every solution found by the algorithm along the calculation timeline in hours is shown for Scenario P_{50} with complete information. The figure highlights that the CP approach does not improve the result linearly but rather in batches with no improvement in-between. At an early stage in the optimization process this behavior makes any assumption on the quality of the result challenging as no asymptotic behavior is visible.

Especially at the beginning, CP is able to constantly improve the result and in total, 45 solutions where found after 4h with an improvement from 259 to 214 missed AVPS. Whereas the next 4 hours provide no new solution, the objective is at 210 after 10 hours and at 192 after 850 hours. Consequently, there is a need to determine a cut off point, as an optimal solution was not found within the first 1000 hours. We used 4 hours for our optimization problem with perfect foresight, as it provides sufficient results with tolerable run-time.

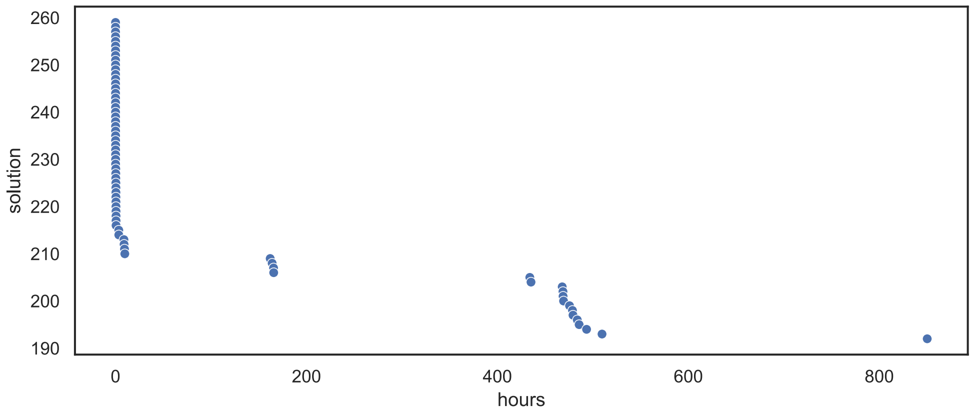

Figure 7.11.: Results with maximum foresight over time

7.6. Discussion

In the AVP setup and for the optimization problem, we make several assumptions that are discussed in the following. We focus on the successful scheduling of AVPS and provide a novel OFJSP modeling approach. Nevertheless, there are additional aspects of the *Services* subsystem that need to be addressed in future research, such as the interaction of the customer with the service subsystem. Building on the communication of the AVP system that enables the drop off and retrieval of the vehicle, the user needs a possibility to communicate the demand for services. The setup selected for this study assumes that customer requests are deterministic and do not follow any uncertainty. In a real world setup, customers might not know their exact departure time in advance or the planned departure can vary over time. Future research should address this issue and develop a stochastic extension of the OFJSP. The OFJSP introduced in this study includes the requirements of an AVP system and uses constraint programming to determine a valid and optimal schedule. Constraint programming was selected as it is a good fit for the JSP (Da Col and Teppan, 2019) and due to its ability to include further constraints (Beck et al., 2011). Nevertheless, we acknowledge that other solving approaches can lead to equal or better results and should be analyzed in future research. The last limitation of our setup is the focus on the pure maximization of scheduled AVPS. The aim of this work is to explore the possibilities of AVP in combination with services and to provide new insights into the advantages of automation in a car park. Yet, we do not include an economical evaluation for both the installation costs of additional service stations and we disregard the potential revenue linked to every successful AVPS. This should be addressed in future work.

7.7. Outlook

There are several adaptations of the JSP discussed in literature and, both, the problem formulations as well as the solver algorithms constantly evolve to include the requirements of new use cases. The novel OFJSP introduced in this study contributes to this line of extensions and future research can build upon our approach to improve run-time and consequently the quality of the results even further. Our analysis shows that very long run-times beyond what is acceptable in an online setting, still lead to an improvement of the results. Due to the innovative nature of the AVP and the extension with AVPS, there is little insight on the user acceptance of such systems. The scheduling approaches provided in this study differ in their ability to provide feedback to customers on which AVPS will be handled upon departure. Whereas the FCFS heuristic determines the success of an AVPS at arrival, the OFJSP constantly updates the schedule over time. Here, additional research is needed to achieve a deeper understanding of customer needs and acceptance.

7.8. Conclusion

In this study, we introduce an extension of the Flexible Job Shop Problem (Online FJSP) to apply it in the online setting of an Automated Valet Parking (AVP) setup with the possibility to provide services (AVPS) to vehicles while they are located at the car park. Further, we introduce a new subsystem that combines the tasks associated with AVPS and define the process from the customers' as well as the a car park operator's perspective. We benchmark the developed scheduling algorithm OFJSP against a First-Come-First-Served (FCFS) and a Random heuristic. The results show that the OFJSP provides the best results in times of low and medium occupancy of the car park, but does not scale well. The run-time of the FCFS heuristic on the other hand is not affected by increasing AVPS requests and provides results in the range of the OFJSP. The results provided by the Random heuristic are inferior to both the FCFS heuristic as well as the OFJSP in every scenario and hence should not be considered in a real world implementation of an AVP system. In addition to the scheduling approaches, this work introduces two benchmarks to quantify the benefit of AVP systems as well as to assess the impact of the online operation. To answer Research Question 5, a lower benchmark without automation is used. The results show that including AVP in a car park can increase the number of scheduled AVPS by at least 46.4% and up to 339.1%, which is a strong indication for the the potential of AVP systems. For the upper benchmark, we use complete information on future customers to identify the upper limit of successfully performed AVPS. The results indicate that there is still potential to improve the scheduling approaches, for example, by including forecasting techniques or stochastic optimization.

In conclusion, this part demonstrates that the potential to coordinate charging behavior using technology available today, as demonstrated in Part II and Part III, can be improved using future technologies, such as AVP. Especially the potential to relocate a vehicle after a service is completed provides great benefits to car park operators and CPOs. For users, the availability of AVP at a car park provides multiple benefits, such as the comfort of receiving different services without direct interaction with either the vehicle or the service station.

Part V.

Finale

Chapter 8.

Conclusion

This dissertation contributes to a successful adoption of EVs by providing novel approaches for charging strategies and locations for EV charging infrastructure that help crossing the chasm between the early and mainstream market. EVs are proven to be a successful measure to reduce GHG emissions (Moro and Lonza, 2018; Falcão et al., 2017) and should therefore replace current ICEVs in order to mitigate climate change. Nonetheless, EVs are considered an innovation that requires users to change their behavior. This is due to the longer charging times of the vehicles and the reduced range. To address this, the Technology Adoption Life Cycle is used to identify the needs of customers to achieve acceptance of the new technology. Here, the success of an innovation is dependent on whether it is able to cross the chasm between the early market and the mainstream market. This can be achieved if the innovation is modified to be *behaviorally compatible* (Gourville, 2005). Whereas due to technical limitations of the vehicle, EVs might not be used in the exact same way as ICEVs in the short term, this dissertation provides novel approaches to integrate the user's behavior into the decision process for the location of new charging stations as well as into charging strategies and therefore makes the switch from an ICEV to an EV *behaviorally compatible*.

8.1. Summary and Implications

The characteristics of charging an EV differ from the process of refueling an ICEV both in time and location and therefore require new solutions and strategies to integrate charging sessions into the current mobility patterns of users. Using ICEVs, users visit a public refueling station once the tank is depleted. Whereas EVs can also use public charging stations, they also benefit from the wide availability of electricity in today's society. This allows for a development of charging strategies that utilize a broad range of locations visited by EV users, for example, at a private home or the destination of the trip. Besides possible locations for charging an EV, the requirements and mobility pattern of the user of the vehicle have to be considered. In Chapter 1, the user groups as well as the locations for recharging addressed in this thesis are introduced and the structure of this dissertation is presented. To gain detailed insights into the requirements of the users of EVs as well as the market participants involved in the deployment of charging stations, Chapter 2 elaborates on the electro-mobility ecosystem. In the following, this dissertation answers a total of five research questions as part of the three main areas of contribution.

First, the challenges and possibilities for private EV users when charging an EV are evaluated. Based on empirical data of the mobility patterns of households in Germany, Chapter 3 analyses the possibility of sharing private charging stations in an urban environment. The home base is a frequently visited location and consequently, no additional trips are necessary when charging at this location. The focus of this chapter is on a novel approach to identify users with complementary mobility patterns that have the potential to share a private charging station at home. The analysis reveals that even a random group of users has, on average, a high potential and in some scenarios is able to cover more than 80% of the distance traveled using electricity charged at home. This result can be improved to more than 90% when assigning users to a cluster based on their driving patterns and matching them with the presented algorithm. Following this approach helps to avoid users simultaneously requesting the charging station and to equally distribute the demand throughout the week. The conclusions of the chapter are limited to a technical evaluation of today's mobility patterns. In order to utilize this potential, further research on the acceptance of users is required. However, the findings also indicate a strong potential to share private charging stations in an urban area and help to address the issue of limited charging infrastructure that comfortably integrates into the users' mobility patterns.

These results are promising for private EV users but, nevertheless, the clustering approach demonstrates that sharing a private charging station at home does not cover the demand of every user group. Consequently, Chapter 4 broadens the scope to public charging stations using an agent based simulation following a Monte Carlo approach. In a first step, generic utilization patterns of possible destinations are evaluated. The results show, that with an increasing dwell time, more demand can be covered, but due to losses associated with blocked charging stations, this effect is reduced for very long dwell times. For charge point operators, this implies that they should focus on destinations with medium dwell times, for example, 16 minutes in the scenario analyzed. For academics, the results demonstrate the importance of including the user behavior at a destination when developing methods for evaluating possible sites for charging stations. While the locations had the same potential demand within the scenarios, the amount covered varied based on arrival rate and dwell time of users. Using real world data of utilization patterns in the city center of Karlsruhe, the results further show that supermarkets have a high potential for destination charging as they are both compatible with the mobility patterns of users and also allow a high economical potential for charge point operators. The simulation focuses on the behavior of users and does not include factors such as the availability of parking lots or the general attractiveness of the location. However, the results also show that even if all supermarkets are assumed to have the same number of customers and parking lots they cannot be seen as a homogeneous group as considerable differences among them exist. Overall, the results of both chapters show that the chasm to the mainstream market can be overcome, when intelligent strategies are used for sharing a private charging station or providing public destination charging. Based on empirical data of trips recorded, private vehicle owners have the potential to make a switch from an ICEV to an EV without the need for a behavioral change.

Part III shifts the focus towards commercial fleets. Here, the vehicle is in possession of an institutional user and the user is, for example, an employee. Following the same differentiation as in Part II, Chapter 5 analyses the potential of private charging stations at the organization's depot. From the perspective of a fleet manager, a decision support system is developed that provides insights into the fleet's ability to be electrified and suggests a suitable charging strategy. Further, a framework is introduced that differentiates between the impact of missed trips due to infrastructure and charging strategy limitations. The results show that 67% of fleets have a close to optimal charging schedule using a First-Come-First-Served heuristic, which requires minimal behavioral change from the vehicle user. For the remaining fleets, the decision support system suggests whether a different charging heuristic provides better results or if foresight on future trips can help scheduling charging sessions. An optimization problem is developed that provides the optimal charging strategy within the available foresight of the fleet. With 73% of fleets improving the share of successful trips with a foresight of 60 minutes, the results indicate that fleet managers should invest in solutions to plan future trips in advance. For academics, the results demonstrate an urgency to predict future mobility needs of a fleet. The charging strategies and infrastructure discussed in this chapter define a lower bound for the electrification of a fleet and assume a strict allocation of a vehicle to a trip. Consequently, charging strategies that consider the interchangeability of similar vehicles might help to improve the results even further. However, regardless of the charging strategy, the results also show that only a small share of fleets can fulfil all trips using EVs, leading to a demand for public charging infrastructure.

Chapter 6 addresses this issue by developing charging strategies that include public charging infrastructure into the operation of a fleet, which is simulated using recorded taxi ride data. Due to uncertain customer requests, taxis might not be able to cover a shift with the range provided by their EV. Based on empirical data from Chicago, an agent based simulation is designed that provides an economical evaluation of the electrification of individual taxis. The results show that private charging of electric taxis is insufficient for most taxis and creates a loss for the drivers. In order to increase the operational return of taxi drivers and hence, to foster EV adoption, the results provided by the simulation show, that the exclusive use of private or public charging infrastructure does not provide optimal results. It is rather the combination that allows 76% of taxis to operate with a positive operational return. Further, the results show that in order to increase the financial return of taxis, the construction of charging stations at frequently visited locations provides the highest improvement. Overall, the results of this chapter demonstrate that the limitation of integrating charging sessions into the current mobility pattern can be compensated due to lower operational cost using the appropriate charging strategy. However, the analysis does not include the investment needed to provide the appropriate private charging infrastructure, which is needed to determine a complete business case for electric taxis and should be addressed in future work. Using empirical data, Part III demonstrates that even though the requirements and mobility patterns of commercial fleets are diverse, there are possibilities to identify those fleets that can adopt EVs today without the need to change their behavior. For the remaining fleets, there are strategies to counter the remaining challenges, for example, using foresight or additional charging infrastructure.

Based on the results of the previous two parts, Part IV transfers the findings into a future use case that allows vehicles to be relocated within a car park. Both private and commercial EV users are negatively impacted by blocked charging infrastructure. Here, automated valet parking allows a car park operator to relocate vehicles once the charging session is completed, leaving room for further customers. Such a scenario allows the possibility to provide additional services besides charging, such as cleaning of the vehicle or deliveries into the trunk. From a car park operator's perspective, this requires the development of a platform that schedules all service requests in real-time while considering the technical limitations of the service providers as well as the mobility patterns of the users. Within Chapter 7, a novel extension of the Flexible Job-Shop Problem is developed and validated using an agent based simulation. The results show, that the online extension of the flexible Job-Shop Problem provides the best results for low and medium utilization rates of the car park, but does not scale well due to run-time restrictions. Further, the results of the simulation show that a simple heuristic such a First-Come-First-Served strategy can provide good results and should also be considered for a real world implementation. The assumption within the simulation is that there is no information available on the future arrival and demand of customers. Consequently, the presented results can be improved using forecasting approaches that predict potential peak demand of services. Overall, the results show that automation of vehicles provides a great benefit to EV users as at least

46.4% and up to 339.1% more services could be provided in the simulated cases. For car park operators, this highlights the immense potential of automated valet parking, especially when combined with a service infrastructure.

The findings of this dissertation can be used to cross the chasm between the early and mainstream market and hence to foster EV adoption. Within five different use cases, new solutions to design charging strategies and to identify the location of new charging infrastructure based on empirical data of user behavior are developed and evaluated. The results can be applied by private vehicle owners that want to share a private charging station, by charge point operators seeking to expand their network and commercial fleets investing in charging infrastructure on their premises or charging at public charging stations. The findings of this dissertation contribute to a *behaviorally compatible* switch towards EVs and, therefore, help to contribute to the reduction of greenhouse gas emissions.

8.2. Outlook

The contributions of this dissertation provide new insights into the development of charging strategies with a focus on the underlying user behavior. Even though five different use cases are presented, there are further opportunities for additional research. In the following, an outlook on potential future research is presented.

Using empirical data provides many benefits, as it describes an accurate mobility pattern of users. Nevertheless, the data analyzed within this thesis is limited to a specific region or city. Whereas Chapters 3, 4 and 5 use records of trips within Germany, Chapter 6 is based on trip data from Chicago. As indicated by Sierzchula et al. (2014), there are country-specific factors that help to explain national adoption rates of EVs. As a consequence, there might also be country-specific mobility patterns that require charging strategies that are adapted to the needs and characteristics of different regions. To verify the findings of this dissertation, further research should include internationally available data sets and research the impact of local peculiarities. Besides the use of regional data sets, it is also important to determine whether the data allows a prediction of user behavior. The results of Chapter 5 demonstrate, that foresight can improve the quality of a charging strategy. Consequently, there is a need to learn the users' behavior, for example, by applying artificial intelligence techniques, such as pattern recognition.

Further, this dissertation focuses on short term solutions for crossing the chasm between the early and mainstream market and consequently, the technical characteristics in this dissertation are based on charging infrastructure and vehicles available today. This approach ensures a straightforward application of the results but might not adequately represent the future potential of EVs. As demonstrated in Chapter 7, technical progress, such as autonomous vehicles, can provide benefits to the EV ecosystem. Improvements in charging speed, as an example, might allow an extension of public destination charging to locations with a shorter dwell time or a more suitable integration of charging sessions in the mobility patterns of taxis. Consequently, as the field of EVs is still developing, further research should extend the simulations to incorporate the technical development of the future.

The approaches presented in this dissertation are based on empirical data in order to ensure that mobility patterns from today's users can be fulfilled using EVs. The charging strategies presented are developed with a technical perspective that respects the constraints of EVs. To guarantee their success, further research on user acceptance regarding the presented approaches needs to be conducted. As an example, EV users might be able to share a private charging station and successfully operate all their trips, but still do not accept the neighbor's vehicle being parked on their premises. The same might apply to commercial fleets, where an optimization, as presented in Chapter 5, can provide an optimal charging schedule, but is not preferred by users due to its higher complexity. Future research should address this gap using, for example, surveys or pilot projects. Further there is a great potential to develop new charging strategies together with the user. Potential users of EVs could participate in the process of developing charging strategies, using approaches from citizen science. Consequently citizens can support researchers to develop charging strategies that are in line with user requirements.

Crossing the chasm between the early and mainstream market is an important step within the TALC and is therefore within the focus of this dissertation. Nevertheless, the life cycle does not end with the early majority and extends the market share towards the laggards. The laggards, or skeptics, are the most difficult customers to reach and hence might require additional benefits associated with replacing an ICEV with an EV. The findings of this dissertation already show the potential of EVs to not only replace ICEVs, but also to provide new benefits not available within the ICEV ecosystem. As an example, Chapter 3 demonstrates that the demand for refueling can be reduced and Chapter 6 shows that taxis can even increase their financial return. Nonetheless, there is more potential within charging strategies for EVs to provide a wide range of benefits to its users, for example through vehicle-to-grid or vehicle-to-home technology. Assuming that EVs are capable to feed energy back to the home or grid allows for completely new use cases, such as back-up power. Therefore, the presented approaches should be extended to use the flexibility provided by users to further improve the benefits associated with driving an EV and consequently ensure a wide adoption of EVs starting from the innovators and including the laggards.

Appendices

Appendix A

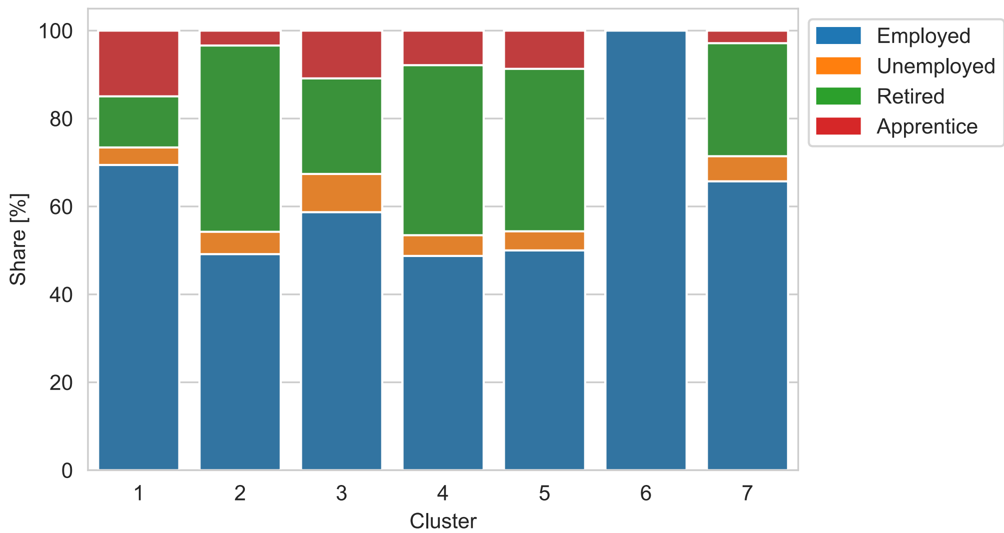

Figure A.1.: Distribution of Employment within Clusters

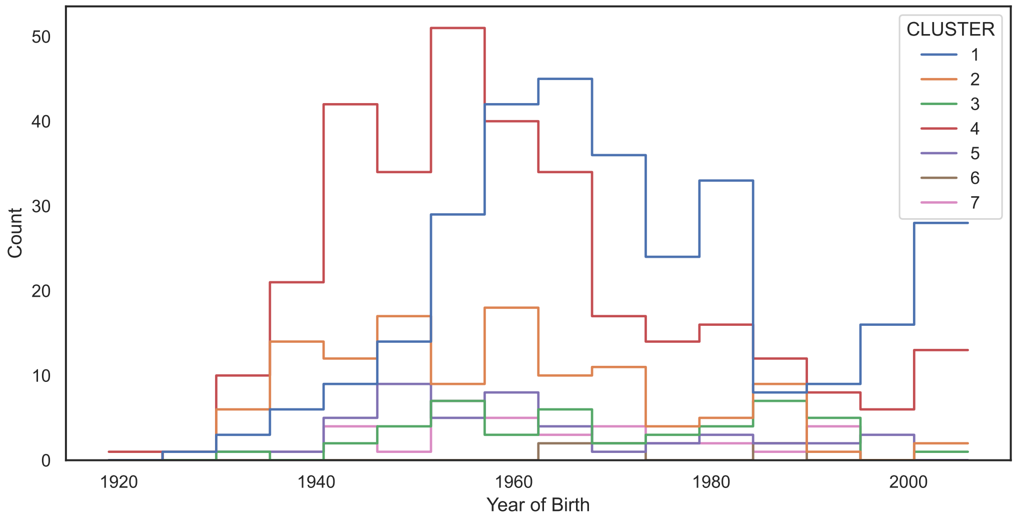

Figure A.2.: Distribution of Year of Birth within Clusters

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