Karlsruher Institut für Technologie

At Home and yet Public

-Shared Charging Infrastructure in Urban Areas-

Bachelor Thesis

by

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Acronyms

Electric Vehicle (EV)
German Mobility Panel (MOP)
First-In-First-Served (FIFS)
Highest-Mileage (HIMI)
Shortest-Timehome (SHTH)

0 Abstract

In a fight against rising global temperatures, politics count on electric vehicle (EV) potentials to reduce emissions. However, the increasing charging demand for these newly introduced EVs is not satisfied in predominantly urban areas (Hardinghaus et al., 2019). City planners are challenged to expand the needed charging infrastructure to meet the demand and rely mainly on public charging stations as the standard solution (Wagner et al., 2014; Adenaw and Lienkamp, 2020). Nevertheless, only 3-8% of all monitored charging events take place at a public charging station (Bruce et al., 2012). Charging at home/work remains the preferred solution (Jabeen et al., 2013). Although EVs do not charge at a private charging station the majority of the time (Lucas et al., 2019), which leaves unused charging slots, while others can not access a charging station. This study combines these two phenomena and shares the unused charging slots within a selected charging collective to create a beneficial shared charging concept for both sides. Driving behaviors from 534 households in urban areas from the county Baden-Württemberg of Germany were utilized for this assessment. To take advantage of the opportunity of shared charging, this work relies on identifying similar driving behaviors along with establishing beneficial charging collectives through a self-created matching process. The resulting charging collectives are then tested under three different charging strategies to obtain knowledge about their technical feasibility. In the framework of this thesis, scientific proof is found that sharing a charging station within a large charging collective is indeed possible in urban areas. Hence, demonstrating an alternative approach through the creation of fixed charging collectives for the expansion of charging infrastructure.

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1 Introduction

Human caused fossil fuel combustion remains the single largest influence on the climate (Quadrelli and Peterson, 2007). Over the course of the past two decades, the global community has acknowledged the pressing need to collectively address and reduce the CO2 emissions caused by fuel combustion (Quadrelli and Peterson, 2007). Germany, especially, is responsible for a very high share of 20% of its energy-related CO2 emissions caused by the transport sector (Pehnt, 2020). Since 184 states declared the environmental protection to international law in the Paris Agreement (Agreement, 2015), Germany responses with specific laws to reduce the CO2-emissions for the transport sector (Bundesministerium für Umwelt, 2020). These policies and climate strategies consider the electric mobility as a promising technology to achieve national climate goals. In detail, EV reduce local emissions in especially urban areas (Richardson, 2013; Perujo et al., 2011) alongside the beneficial effect of shifting emissions from the transport sector into the electricity sector (Pehnt, 2020). Moreover, (Richardson, 2013) concludes that coupling this effect with a higher integration of renewable energies could reduce the CO2-emissions of multiple sectors. These promising benefits together with the newly established policies might have pushed innovation and fundamental rethinking of modern mobility into the automobile industry to invent viable approaches for the future. Volkswagen, as a global player, shows that the automobile sector strives for innovative ideas in order to achieve the lawful emission limits for their product portfolio. They radically restructure business segments purely to produce EVs. This outlook is so predominant that, the strategy "TRANSFORM 2025+" to electrify the whole product portfolio is forced to pace with an additional strategy "ACCELERATE" in order to stay international competitive (Newsroom, 2021). In aspect of the specification of EV, local areas are considered to be the best suiting environments to use electric car mobility when focusing on daily needed short range Nobis and Kuhnimhof (2018). Nonetheless, the supporting charging infrastructure is underdevelopment, which raises major concerns for the large-scale deployment of EVs (Deb et al., 2018). In detail, the integration of the promising EV along with their multiple benefits encounter a complex mix of obstacles that cause range anxieties (Morganti and Browne, 2018). Some are identified to have missing economical incentives for the high investment costs for EV (Thiel et al., 2010; Bühne et al., 2015). However, the most significant obstacle is the missing access to charging infrastructure, which sufficient access reduces the cause of range anxieties upon the existing and the potential EV-owners (Neubauer and Wood, 2014). Furthermore, these obstacles have the possibility to additionally inhibit a larger market penetration for EVs, according to Steinhilber et al. (2013). Therefore researching solutions for the future charging infrastructure is a crucial step to reach the set climate goals.

1.1 What is the Missing Link?

To reduce the increasing charging demand, multiple debates are raised to discuss mobility needs in European metropolitan areas through the expansion of public charging stations (Frade et al., 2011; Hardinghaus et al., 2019; Wagner et al., 2014). In Berlin, rising demand for charging opportunities in especially urban areas is observed by Hardinghaus et al. (2019). The same issue faces the city of Lisbon (Frade et al., 2011). The author discovers that cities, which were mainly developed before car mobility, lack parking spaces for the general public. Therefore they rely strictly on the expansion of centralized public charging stations. Except charging at public places is the least favorite, as shown in the British project CABLED, where only 3-8% of the monitored charging events took place at public charging stations (Bruce et al., 2012). Furthermore, the optimal distribution of public charging stations, together with local demand, pose high realisation obstacles for city planners (Wagner et al., 2014; Adenaw and Lienkamp, 2020). Relying on the centralized approach seems inadequate due to its minor acceptance. The availability of private parking spaces and, therefore, the installation of wallboxes is a crucial factor that influences the readiness to purchase EVs (Patt et al., 2019). It has been shown that EVs park mostly in private parking spaces to use their private charging stations (Nobis and Kuhnimhof, 2018). Above all, households with the ability to install a private charging station, which is also called a wallbox, are twice more likely to purchase EVs, according to Patt et al. (2019). This is probably why nearly 90% of all charging events took place at a private charging station at home (Österreich, 2020). However, the majority of urban residents live in collective buildings without private parking spaces and face hard limitations to install adequate private charging stations, which is noticed by Petit and Hennebel (2019). These challenges can vary from economical to technical nature (Steinhilber et al., 2013). On the economic side, the additional cost of EVs and their longer payback periods, compared to conventional combustion vehicles, will stay an issue for the near future (Thiel et al., 2010). Examples of technical challenges are parking garages, where constructions are often hindered by regulations. Further limitations are the absence of private parking space, where urban residents often compete in a first come first serve environment when it comes to their preferred parking space. Solutions for these urban residents living in collective buildings must be proposed (Petit and Hennebel, 2019). Simultaneously, charging at home/work remains the predominant solution (Jabeen et al., 2013), although EVs spend more than half of their time at their charging station without charging (Lucas et al., 2019). In this regard, could these two phenomena, that a high charging demand is present in urban areas and that wallbox-owner have unused charging times, be beneficially united?

1.2 Literature Review

Shared charging concepts seem to be the solution. They potentially combine the comfort of charging nearby or at home and additionally create financial benefits by splitting costs. Above all, they can satisfy the charging demand of larger groups and thus help to reduce the increasing charging demand in urban areas. Nevertheless, the topic of sharing concepts is sparely debated in the scientific community. Reviewed studies apply shared charging in two different approaches.

Some cover mileage by sharing EV fleets. Their concept is based on having an accessible EV fleet for a community. EVs that are not used are charged in advance to provide the needed mileage. Song et al. (2019) provides an operating and planning concept for such communities in the residential and business sector. Moreover, Jia and Wu (2021) provides a complex scheduling algorithm to solve the scheduling issue that occurs by integrating renewable energy sources to charge the shared EV fleet. Further ideas to solve how EVs get to the charging stations utilizes current innovation of the upcoming autonomous cars (Leiding, 2021; Zhang and Chen, 2020). These EVs optimize their unused time for charging events. According to Roni et al. (2019), the limiting factor of these concepts is the accessible charging infrastructure, in which the author assessed the downtime of free-floating shared EV-fleets upon different charging stations allocations.

Others utilize the benefit of a shared charging station. To clarify this approach, Aichmaier and Ludwig (2015) describe an example demonstrating how nearby neighbours could share charging infrastructure. Their so-called "intelligence wallbox" is set to overcome local barriers and achieve national to supranational goals. Research papers have been published in a large span from local to national applications. Starting at the top of this span, Koç et al. (2019) examined their extended EV routing problem and considered investment costs for additional charging infrastructure to minimize opening costs and drivers costs. In addition to coordinating larger-scale groups Chen et al. (2022), introduced hierarchical scheduling on shared charging stations to meet the charging demands of the EVs. The author concluded that estimating charging time and coordinating charging periods show extensive potential. Others achieved to reduce the waiting and charging time significantly through a shared charging concept (Wang et al., 2019). Wang et al. (2019) utilized the heterogeneous patterns of large groups, which consists of e-taxis and e-buses. Their different mobility and charging patterns allowed to schedule their charging slots through a fixed timetable.

Concepts that focus more on the residential sector and the direct benefit of individuals in a charging community are those of Azarova et al. (2020) and Kostansek (2021). Kostansek (2021) analyzed already existing private charging stations in the county of Salzburg in Austria to take care of people with no installation possibili-

ties for wallboxes at their residential buildings. The author mainly dealt with the idea of utilizing shared charging as an additional supply to satisfy charging demand and analyzed the potential. These shared charging stations have no fixed membership and work of the principle that the general public accesses free charging slots (Kostansek, 2021). The author concluded that giving broader access to an already existing charging infrastructure can, in the long term, expand the charging infrastructure through additional participation of the citizens. All these charging stations are within walking distance and show the great potential of making nearby charging infrastructure more accessible.
Similarly, Azarova et al. (2020) assessed a business model that combines the advantages of private charging with the cost savings of joint purchase between households in Austria. The author concluded that understanding the preferences of individuals is important to configure the community financed charging concept. These preferences are identified by a survey and only reflect self-aware preferences of charging. Moreover, participants are clustered by income together with ownership of an EV. Creating a business model, which uses the concept of a community-owned charging station, is plausible for the author. Important factors are the relationship within a group alongside the size of the community. The reviewed literature provides ideas for sharing concepts with different set goals to support electric mobility. The interesting possibilities of sharing concepts on a local or global scope inspire this work. However, the presented sharing concepts deal more with the beforehand assumed charging collective and their resulting potential benefits rather than providing the detailed creation of a charging collective. This study contributes to the configuration of the charging community by focusing on the driving behavior to bridge the gap in the technical creation and feasibility of shared charging infrastructure. To get there, the work adds to the business model of Azarova et al. (2020) and identifies driving behavior in order to configure beneficial charging communities in nearby areas. Although Kostansek (2021) does not assign citizens directly to charging stations, the approach of this thesis could improve the author's idea through sharing the charging infrastructure more efficiently. The other parts of this work add to maximising the size of the charging community to possibly utilizes higher participant number in the business model of Azarova et al. (2020) without loss in mobility. Furthermore, this thesis gives additional information if the approach to utilize heterogeneous driving patterns in the public transport sector can be implemented in the residential sector, which contributes to Wang et al. (2019).

Therefore, this thesis fills the gap in the literature on how a shared concept for a charging community is technically implemented while also identifying beneficial configurations of the charging communities. For this approach, current technical boundaries of private charging stations ,respectively, wallboxes are considered.

1.3 Objective of Research

The subject area of this thesis is located in the research field of sharing wallboxes within communities or, respectively, collectives in urban areas. Apart from other studies in this field, this thesis focuses on the challenging part of creating beneficial charging collectives and assessing the technical feasibility of a shared charging concept within a charging collective. In general, examining innovative ways to provide the comfort and availability of charging at home solutions for a greater number of people through a shared charging concept. This concept creates a nearby accessible charging station for the founded charging collective. In this point, the work differs from Kostansek (2021), because the shared charging concept of this work creates fixed charging groups and does not examine nearby accessible charging stations for the charging collective. Apart from this, the elaboration of this thesis aims to add to the author by improving the shared charging concept through the matching of specific driving behaviors. These resulting advantages give broader access to wallboxes, thus expanding the accessible charging infrastructure on a larger scale. Each individual willingly participating in the sharing concept aspires to the same goals, hence why the charging community is called a charging collective. Such a charging collective is sketched in Figure 1. It is only focused on solely battery-powered electric vehicles to have clear causes on the incurring charging demand, which is not granted by other types of electric vehicles, for example plug-in electric vehicles that also rely on fossil fuels. Therefore the assessment of the technical feasibility has a clear cause. On the economic side, establishing a business model is not a part of this thesis. The approach to split costs under larger numbers of participants is the only reducing factor of investment and operation cost that is taken. This is done accordingly to Azarova et al. (2020), in which charging costs are divided between more participants for the installation and operation of the wallbox. Kostansek (2021) adds that the wallbox provider could even demand financial compensation for the use of the wallbox. Therefore, relieving wallbox-owners from high investment and operation expenses and simultaneously increasing financial incentive by splitting costs to form a suitable solution for the economic barrier of electric mobility. On the technical side, obtaining valuable information on the feasibility of sharing a wallbox in a collective is the core element of this study. In detail, the thesis assesses the following steps in order to acquire the needed information to fill the gap in the literature. The first step is understanding the driving behavior in urban areas through a clustering of the data set. In this regard, the following research question is answered.

- Which distinguishable driving behaviors exist in the scope of the data set?

Other than Azarova et al. (2020), this thesis uses real-world mobility data rather than inspecting socio-economic data. The resulting clusters of the clustering create the basis for this elaboration. Secondly, different charging collectives are established with distinguishable properties. One utilizes a matching process in order to merge beneficial behaviors to multiple matched groups. The other one randomly selects individuals from the data set to form groups. Furthermore, these groups are tested on three charging strategies. Key performance indicators for the charging simulations are assessed to acquire precise information about the following two research questions.

- Is the matching of charging collectives more beneficial in terms of charged mileage of a wallbox than randomly chosen collectives?
- To what extent can a collective of households share a charging station without significantly influencing their daily driving behavior?

Hence why, this thesis creates the scientific-technical basis to institute collectively shared charging infrastructure in urban areas with the goal to satisfy charging demand and to overcome economic together with technical barriers of electric mobility.

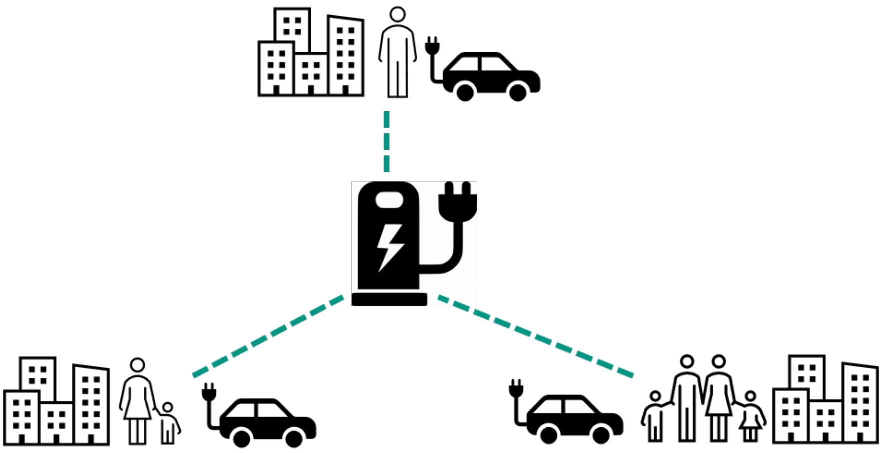

Figure 1: Visualized charging collective.

2 Data and Methodology

This section is separated into four parts and constructs the methodology of the thesis. First, the utilized data set is described in detail. Secondly, the clustering methodology is described extensively along with the selected segmentation variables. Thirdly, the matching procedure is presented to merge the in advance identified driving behaviors into matched groups. Finally, three charging strategies are simulated on the matched groups and the randomly selected groups to obtain valuable information about their performances and beneficial properties.

2.1 Description of Data

Table 1: Calculated Variables from MOP.

Calculated Variables	Description
Timehome	Parking duration at home
Tripduration	Car trip duration
Timeelsewhere	Parking duration elsewhere (not at home)
Tripcount	Total number of trips per week
Roundtripcount	Total number of round trips per week
Mileage/Trip	Driven mileage per trip
avgStart	Average start time of round trips
avgEnd	Average end time of round trips

The used data is from the German Mobility Panel (IFV, 2018), starting in the year 2017 and finishing in the year 2018. The mobility data reflects the driving behavior of German citizens. Each mobility event in the data set is collected through a questionnaire. The filtered data set only includes mobility data by car from households, which are primarily located in highly populated urban areas in Baden-Württemberg. The mobility by car is described by driving events from one specific week with seven consecutive days by a household. Keeping in mind that this study aims to solve car mobility needs of households, mobility data from individuals of one household is summarized into their unique household-ID with different individual identification numbers. Subsequently, the data includes 534 households with 874 participants. In order to make a future analysis clearer and more understandable the trip data of the following seven days, which were raised on different dates, is modified to fit into one week without risking corruption of the data. Additional information to supplement the mobility data is further provided by other data sets of the MOP. These give access to the purpose of each trip as well as the socio-economic details of the household and individuals. The later examined variables are calculated by using existing information from the questionnaire. Main elements for describing parking and driving events are summarized by the following variables in Table 1.

2.2 Methodology of Clustering

In this section, the algorithm-supported clustering takes place. To reveal hidden relations between the high sum of data points, the programming language Python is used. The goal is to find households with similar driving behavior and assign them to the same cluster center by analysing their characteristics in the scope of the selected segmentation variables. The approach of the clustering is based on the idea that driving behaviors are measured by the selected segmentation variables (Halim, 2016). To carry on doing so, it is assumed that the examined driving events over a full week represent the everyday driving events. Hence why, the selected variables are assumed to provide an accurate measurement in the limits of the used data set. Given that the trip data had been set by conventional cars, it is assumed that vehicle owners use their EV in the same way.

Being mostly inspired by the approach of Sodenkamp et al. (2019) and partly inspired by the selection of the clustering algorithm from Halim (2016), the clustering of this study shares the trusted procedure to identify different driving behaviors from a data set by choosing a similar methodology. Both authors rely on different inspected data specifications and goals compared to this study. Starting with the included variables, the most important properties of the driving behavior resemble the segmentation variables. Sodenkamp et al. (2019) chose specific variables for their clustering. These are divided into variables that assess the distance of trips, the number of trips and the driven speed. Variables that capture the duration of driving activities are the parking duration and the trip duration. The leftovers are calculated ratios between the already mentioned summarized variables. Given that the used data set for this thesis does not have the same data base, the selection for this thesis is altered. Nevertheless, the selection process is orientated towards the research of Sodenkamp et al. (2019).

An inspection of the data set showed significant alteration in the variables on weekends compared to workdays. That is why variables are temporally separated into workday and weekend times.

The first variable describes the mileage per home-to-home round trips (Mileage/Trip). This is later useful to estimate the charging duration, since every driven kilometer has to be recharged. The second variable is the time at home duration (Timehome), also split into workdays and weekends. It gives important input on the possibility of postponing charging events through the fact that individuals with a long spent time at home have more possibilities to schedule their charging events. The contrary to this variable is the time spent elsewhere (Timeelsewhere), which includes the time that is not spent at home or during driving. The last inspected duration gives valuable information about the actual driving time(Tripduration). Continuing to the remaining segmentation variables, which reflect the frequency of trips (Tripcount, Roundtripcount) alongside timestamps (avgStart, avgEnd) for driving events. Each calculated variable is shown in Table 1.

In order to analyse correlations between the sixteen variables, the Pearsons-Bravais-Correlation coefficient is used. Due to strong correlations between variables, the following five are not further considered in the clustering. The said five canceled variables are listed. The first is the Roundtripcount on workdays (correlated with the trip count on workdays, coefficient 0.904) together with the Roundtripcount on the weekend (correlated with the Tripcount on weekends, coefficient 0.900). Secondly, the avgEnd of trips during the weekend is removed (correlated with the avgStart at the weekend, coefficient -0.855). Lastly, the Timeelsewhere during workdays (correlated with Timehome during workdays, coefficient -0.987) and Timeelsewhere on weekends (correlated with Timehome on the weekend, coefficient -0.985) are excluded. Altogether eleven segmentation variables are picked and are displayed in Table 2.

Table 2: Segmentation variables.

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

Each household is described through eleven segmentation variables. Focusing on the whole data set, cloud-like properties are expected. Since the exact shape is unknown the clustering needs to rely on a robust method. Hence why, the Kmeans algorithm, firstly proposed by MacQueen, serves as the core element of the clustering process (Jigui et al., 2008). Discovered shortcomings in efficiency of the Kmeans algorithm by Na et al. (2010) do not influence smaller data sets, which complies with the used data set. By choosing Kmeans, the clustering benefits from a non-biased selection of cluster centers along with the robustness of the algorithm when applied on different shapes of data sets. According to (Halim, 2016) clustering using Kmeans provides similar values in comparison to other clustering techniques. Therefore the selection of K-means is the right choice considering the properties of the data set. The Kmeans-algorithm works on the principle to assign, in this case, households to their most similar cluster center. To measure their similarities, the distance between characteristics in their driving behavior is calculated through the Euclidean Distance. As an outcome, each household is assigned to a specific cluster center together with aspiring a high distinction between the cluster center's properties. However, the number of cluster centers has to be defined in the upfront. Therefore, the first method for choosing the appropriate number of clusters in the Kmeans algorithm is the Silhouette Method (Rousseeuw, 1987). It measures how well data points are assigned to their cluster center by comparing distances to other data points. The silhouette coefficient ranges between [-1,1], with a high value indicating high distinguishable clusters. Additionally, the decision for the amount of cluster center is further supported by the Elbow Method (Bholowalia and Kumar, 2014), which illustrates distinguishing levels of the data set on an interval consistent of cluster center amounts. Moreover, the agglomerate hierarchical grouping, proposed by Jr. (1963), with the Ward's Method specification, is chosen to clarify relationships between the identified clusters. The Ward-linkage between clusters is based on their minimal collective growth of the Error Sum of Squares, thus creating merged clusters with minimal variance. This specification is used to understand relations between the resulting clusters and supports a natural interpretation of the data set.

2.3 Methodology of Matching

This section aims to utilize the full potential of sharing a wallbox. The idea behind this is to find a cluster with complementary mobility behaviors and merge them. This is not only done to create a smooth distribution of mileage per day. It simultaneously provides the possibility to cover higher mileage upon larger charging collectives. A somewhat similar approach was taken by Wang et al. (2019). The author utilized known peaks of charging in shared limited charging infrastructure and allocated these more evenly. For doing so, scheduling the heterogeneous arriving and departing times of e-Bus and e-Taxi fleets was crucial. The programming language Python is applied to create and execute the matching process.

2.3.1 Beneficial Characteristics

It is mandatory that the matched cluster groups fulfill certain characteristics to reach the goals mentioned above. This part gives a general estimation to understand the aspired beneficial features of matched groups in contrast to randomly selected groups. Randomly selected groups have the probability not to suit their appointed participants at all. For example, a randomly selected group consisting only of weekend drivers ends in extremely high demand for charging on the weekend and a mainly unused charging station on workdays. This creates the risk of exceeding the possible charging capacity in peak times along with rock-bottom charging demand on other days. Controlling this risk by merging complementary working participants into groups is the main goal.

This way, two key variables which influence charging are explored. The first key impact on charging duration is the mileage of the home-to-home-round trip. Here described as average kilometers per day that need to be charged after each round trip. A beneficial match is characterised in this scope by an evenly distributed mileage per day. This prevents daily peaks alongside an overall smoother occupancy of the assigned charging station. A simple example for such a complementarily working matched group is a match consisting of a weekend driver and a workday driver. Ideally, they substitute their mileage temporally and thus, their usual charging demand is covered by the wallbox.

The second important variable is the time spent at home (Timehome). This variable determines not only the possibility of charging their needed mileage required for the person's next round trip, but it also serves as an indicator to postpone charging events. Therefore, it functions as a matching factor because participants with a higher Timehome elevate the average Timehome of the collective and vice versa. Ensuring that the participants have a long enough Timehome is the second crucial consideration. The matching process finds a balance between a long enough time spent at home and a smoothly distributed mileage per day. This distribution creates the beneficial properties that this matching process pursuits. Thus, they achieve to charge their needed mileage together with the advantage to split the costs. Creating this without a significant loss in mileage and comfort for the individual is the critical part, even more, when this concept is scaled up to multiple participants in a charging collective.

2.3.2 Assumptions

Before the description of the matching starts, some assumptions are established. Having limited processing capacity, this study is not able to choose the ideal approach to combine and assess each of the 874 participants driving events. Thus the cluster center as the average specification of the clusters is utilized for the matching process to solve the processing limitation. In order to do so, it is assumed that the cluster centers represent the assigned households sufficiently and reflect the long-term driving behavior. Therefore, the matching process is based upon the same assumptions as the clustering process.

2.3.3 Calculating Matched Groups

This part is designed to solve the bipartite matching problem of participants with different driving behaviors. To assure that the mileage of a matched group is theoretically charged, limits are generated. On the one hand, these limits result from the technical boundaries of the used charging setup. As mentioned in the setup assumption, one standard wallbox for home solutions with 11kW and one charging cable is used as a charging station for the collective. With this setup, the daily theoretical upper limit of the charging capacity is calculated and results in 264kWh/day. As stated, the data set has no information about possible EV specifications in battery capacity and consumption. Considering this, the average consumption of an EV from Yuan et al. (2015) with 0.16kWh/km is used as the general basis of assumption. Therefore one wallbox theoretically charges a maximum of 1650km per day (11550km per week). Two limits ensure that the theoretical boundaries are respected. The first upper limit (= 1650km/day) is the maximum chargeable mileage that one wallbox outputs per day. Exceeding this upper limit makes charging with 11kW theoretically impossible. The second limit is the bottom limit (coefficient = $0.0145 km^{-1}$). It guarantees that the collective, on average, spends enough time at home for charging. The bottom limit is called Timehome/km-Ratio and is calculated by dividing the theoretically available Timehome (24h) by the maximal daily chargeable mileage (1650km/24h). These two limits consider that the collective does not exceed the technical charging limits along with not surpassing the needed Timehome for charging their mileage.

On the other hand, the matching algorithm needs to grant the quality of the matched group by complying with the set standards in subsection 2.3.1. The variance of mileage per day is the key decision variable to assess the mileage distribution together with the overall quality of the match. Low variances or relatively low standard deviations of the collective in mileage per day are directly linked to a smooth mileage distribution. The standard deviation is chosen to have a less complex interpretation of the variable. Additionally, the occupancy in the percentage of a wallbox is calculated to provide a visual estimation. The occupancy results from dividing the time one car is plugged into the wallbox per week with the maximum theoretical time per week. It provides valuable information about the usage of the wallbox. Moreover, it shows when the saturation is reached, in combination with the covered mileage. The algorithm ensures that only the cluster center, which creates the lowest collective standard deviation is added to the collective. This provides a beneficial match.

In conclusion, the set limits create the framework in which the inputted cluster centers are selected according to the target function. This allows the merging of larger groups with smaller standard deviations and thus is more helpful in creating larger complementary charging collectives.

Starting the calculation of the matched groups, the following bullet list shows the obeyed limits, the decision variable, and the target function of the matching algorithm. The italic letter in Figure 2 shows where exactly these come into play.

1. *Upper limit:* maximum chargeable mileage per day $<= 1650 km/day$;
2. *Bottom limit:* minimum Timehome/Km-Ratio per day $<= 0.0145 km^{-1}$;
3. *Decision variable:* collective standard deviation of mileage per day;
4. *Target function:* choose lowest collective standard deviation of mileage per day;

The following Figure 2 on page 15 shows the decision-making process in the matching process.

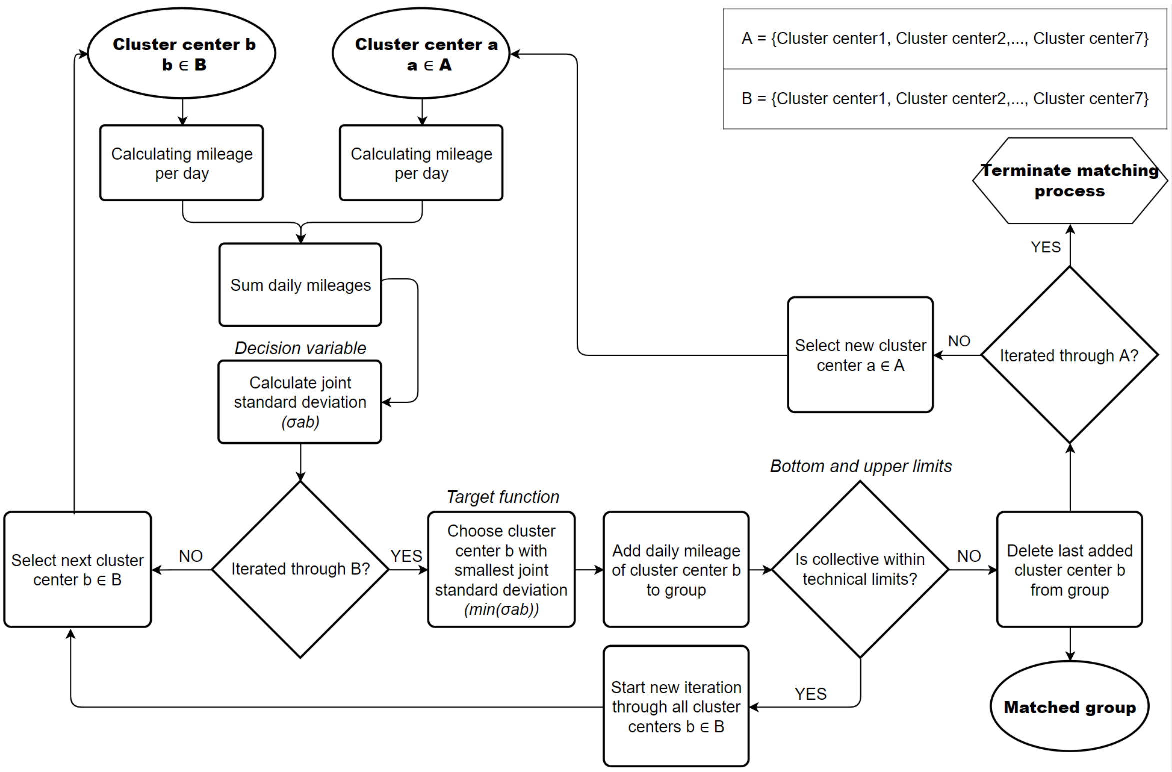

Figure 2: Matching Process.

Applying this to the context of the shown matching diagram 2, the algorithm starts with two sets. Set A consists of all cluster centers like that of set B. The only difference is that set B is repeatedly iterated and set A just one time. In each iteration of the algorithm, the daily mileage is calculated to determine the joint standard deviation of the first combination. This is done until set B is fully iterated on time. From this point on, the algorithm picks the minimal joint deviation along with the related cluster center from set B and adds it to the selected cluster center from set A. This ensures that only matches with the lowest collective variance are created. This smooths the mileage distribution by making use of possible complimentary driving behaviors. This is repeated multiple times until the earlier specified limits are reached. Then the matching process creates one matched group. This is the starting point for the next cluster center in set A to iterate the process once more. The matching process stops when every cluster center from set A is selected. Thus the algorithm establishes larger groups by respecting technical limits alongside merging beneficial complementary driving behaviors.

2.4 Methodology of Charging Simulation

In this section, the vision of the study is directly tackled. A simulation is carried out in order to assess the technical feasibility of the charging collective from an ex-post perspective. The charging simulation is performed in the programming language Python.

2.4.1 Setup and Assumptions

This part establishes the assumptions of the boundaries for the charging setup. In general, this thesis considers mainly the technical feasibility and therefore assumes that striving towards a larger group size increases the economic benefit of individuals by splitting investment and operating costs. Furthermore, it is assumed, for calculating necessity, that the EV is only charged at home for every round trip and is described to be a battery-powered electric vehicle to have a closed charging model, in which every driven kilometer is recharged at the wallbox. Thus every household must have purchased an EV that can achieve their range per round trip. Since this thesis assesses if mobility needs by car can be covered in shared charging infrastructure, the testing of charging strategies works independently from battery capacities. To do so the driven mileage is used in an ex-post perspective to examine the feasibility of the strategy. Hence why, this study is detached from the boundaries of EV specifications and does not need an assumed battery capacity because solely the driven mileage by the household is charged. The charging process starts instantly and stays on the same performance level of 11kW. Thus, the charging setup is free from external influences and works flawlessly. Additionally, the wallbox charges the beforehand driven mileage in the simulation. The number of cars does not impact the test by any means.

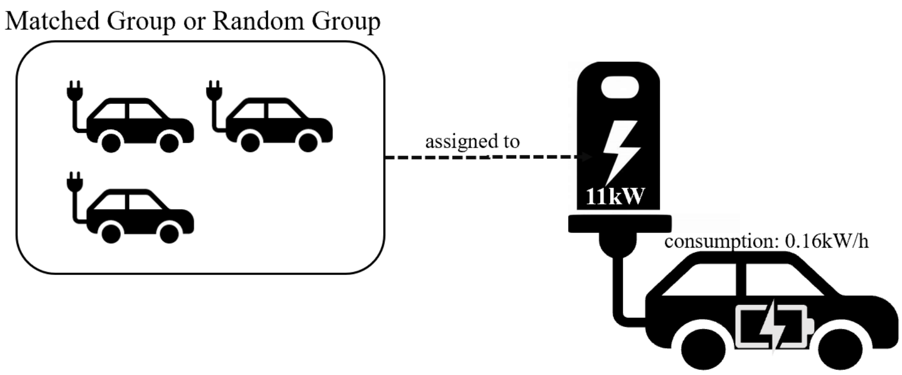

Figure 3: Charging Setup.

To address the expansion of charging stations in urban areas, the key element this thesis utilizes is having the unhindered availability of the wallbox combined with the comfort of charging nearby. Hence this part describes the technical setup to achieve the set goals. The collectively shared wallboxes need a designated location to be installed. Locations as such can vary from privately owned parking spaces to installation possibilities, which are provided by local authorities. Often existing private charging infrastructure can already be used, according to Kostansek (2021). Therefore, it is assumed that each collective has an easily accessible location to install and operate a wallbox, which is assumed to be nearby the individuals of one charging collective. The technical setup per testing group consists of a wallbox with one charging cable and is sketched for the personal idea in section 3. Thus one EV is charged with the full power of the wallbox. As stated above, the setup on the technical side depends on the assumed 11kW performance of the wallbox together with the consumption of 0.16 kWh/km (Yuan et al., 2015) of an EV to calculate charging duration.

The setup is designed to ensure the comfort of the participants. The assigned charging strategy within the collective must cover the car mobility needs of the collective in the first place, while simultaneously being comfortable for all individuals.
This study identifies two factors influencing the charging collective. The first is the disturbing factors for people which have the possibility to install a wallbox at their home or live closely. These are generated through the daily traffic of charging events from the collective. To ensure the comfort of said people, some rules are established in the charging process.
First of all, swapping the car between midnight and 6 am is allowed precisely one time for an arriving EV and then declared resting time. This time frame remains used because of the high potential in covering mileage during these six hours. Another disturbing factor is the high quantity of switching between charging events. This affects the entire collective. For example, both the wallbox container and individuals who live close to a wallbox are disturbed by high charging traffic. Additionally, individuals, which do not live directly at a wallbox, have to travel the distance more often with the frequency of scheduled charging events increasing. Therefore, the frequency of charging events is kept low through a minimal charging duration of 2hours.

The other factor is the additional expenditure that participants need to endure to get to the nearby wallboxes. Because of the charging strategy, participants are sometimes required to plug or unplug their car when they are already at home. This can often be done by arriving participants if the charging events are scheduled seamlessly. To ensure similar comfort to that of a privately owned wallbox, a low frequency of plugging events when no one is around is aspired.
Altogether, the minimal charging duration and the implementation of resting times as well as the investigated quantity of unattended events for switching plugs, are

implemented to strive for a higher comfort level of the collective. However, the lost charging time, which results from keeping the comfort level, causes a trade-off between covering mileage and ensuring the comfort of the collective.

2.4.2 Charging Simulation

The test conditions for each charging strategy are the same. It consists of a group combination, which is selected from two different pools. The first pool stores the matched groups are elaborated in part 2.3.3. Thus, the matched group is created by rules set in advance in order to achieve a beneficial sharing of the wallbox. The second pool contains the randomly selected groups. It reflects the approach that random people meet each other and start sharing a wallbox without researching their individual compatibility in the examined urban area. This creates a suitable reference to evaluate if matching specific driving behaviors is more beneficial than randomly creating charging collectives. Due to this, each matched group is separately evaluated against the random pool. Every group is flexible in its group size to test the influence of different group sizes. The investigated charging collectives range from a minimum group size of three households to a maximum group size of fifteen households, limited to household numbers that are multiples of three due to computing capacity limitations.

Implementing charging strategies on our data set reveals multiple issues. One is the yet limited range of EVs, which is why some trip distances are impossible to travel with a singular charge when considering the trip back home. These trips demand further charging during round trips in a real-world implementation. More interesting is how these trips are considered in the later evaluation of the charging strategy. Therefore each charging strategy has a set of variables to assess its quality. Charging strategies must be suitable to satisfy the mobility needs of the examined households in urban areas. It is, therefore, necessary to find charging strategies that do not restrict everyday mobility in the first place. Hence why, the key performance indicators for each charging strategy are prioritised and assessed in the following order. The first variable is the overall covered mileage, which is the sole indicator of an optimal charging station, therefore a high coverage is pursued. Charging strategies are only considered suitable if they cover more than 90% of the driven mileage. This assumption is based on Greaves et al. (2014). The author finds that average distances below 60kilometers are easy to cover with a simple home charging solution, which constitutes to 90% of the driven mileage. Thus, this sets the benchmark to achieve the same level of covered mileage, like a simple home charging solution for one private household. The second prioritised quality control variable is the additional expenditure due to the high frequency of unattended plug switching when no other participant is around. High amounts indicate additional high expenditures for the individuals of the collective, as they need to be able to get to their wallbox and unplug their car. If a charging strategy is not yet clearly decided on, because of similar values, then the overall occupancy of the wallbox is inspected. In general, a low occupancy is pursued. This creates, in the first place, a comfort factor for the wallbox container and shows how much a wallbox is being used. This way, the curve of the occupancy creates a saturation curve, which is why it is identified how much room is left for additional participants.

The presented charging strategies are separated into three different priority concepts. These priority concepts influence the series of individuals in one group and thus prioritise their charging events. For doing so, certain specifications are taken advantage of. These specifications and series are shown posterior. The body of each charging strategy, where the actual charging is simulated, remains identical in every strategy. It consists of the charging process and three charging requirements for each charging strategy. The charging process works in an ex-post perspective, where it is tested if the driven mileage of the testing group can be covered by one wallbox. Therefore deficit mileage is summarized over the length of one home-to-home round trip and later subtracted over the duration of the charging event. The charging process starts when a participant arrives home and fulfills the charging requirements. Hence, charging is only allowed when every requirement is verified. First of all, the requirements ensure that only one individual charges at a time. In order to reserve a time slot, a participant needs to be at home for the proceeding two hours. This prevents a high frequency of plugging/unplugging of EVs into the wallbox. With the idea to achieve more comfort alongside a more realistic implementation possibility. The third requirement comes into place at night-time between midnight and 6 am, where charging is only allowed for participants who arrive before midnight. These charge their deficit mileage and need to stay until 6 am. This is implemented to protect the comfort of the people that live nearby and of the wallbox container. Said comfort factors are extensively described in section 2.4.1.

2.4.3 Charging Strategies

In literature, some charging models are discussed. The model described in the research from Flath et al. (2012) relies on the "As-Fast-As-Possible (AFAP)" charging strategy, which implies that each EV instantly starts the charging process. This is used to visualize the uninfluenced charging behavior. Therefore this thesis uses the First-in-first-served (FIFS) in the same way as Flath et al. (2012). Others use smart charging to optimize their set goals. Found literature mainly minimizes the cost of charging in complex algorithms (Schuller et al., 2014; Cao et al., 2012). The approach of the charging simulation of this work is to enforce as few rules as possible on the charging collective because too many rules have an unknown impact without proper research. Hence why, it is focused on having more flexible charging choices for not flexible drivers (Flath et al., 2012). Thus the smart charging rules of this study depend on own assessment because the goal of this thesis is to maximize the covered mileage in the first place. Altogether this thesis formulates in addition to the straight forwards FIFS-strategy two smart charging strategies. Theses strategies base their scheduled charging times on two variables, which are considered to mainly influence charging behavior. These are the mileage driven and the time spent at home. All charging strategies are tested in 300 selected groups per pool, which are created according to the boundaries of their assigned pool. After testing, the charging strategies are logically compared based on the quality control variables.

First-In-First-Served (FIFS):

This strategy is based on the idea of first come first served. It means that the driver who is first to reach the wallbox is allowed to charge his needed mileage. Other drivers that arrive later have to wait until the wallbox is free again. Thus in some scenarios, a queue is created. As described, this strategy is applied to provide the unaltered need of the group (Flath et al., 2012). Hence why, this creates a reference for the other two chosen strategies.

Highest Mileage (HIMI):

Starting with the first smart charging rule, the testing group is sorted by their weekly mileage. The household with the highest mileage is the first to be allowed to schedule their charging events in the week. The same approach is used to schedule all remaining charging events to ensure that, in the end, the participant with the lowest mileage can only access the wallbox in the remaining slots. It is logically derived that mileage has a direct influence on the charging duration. The idea for this prioritised access is to focus on covering the highest mileage first and thus the longest charging duration. The leftover charging slots are then assigned to a shorter charging duration. This is an effort to increase the covered mileage.

Shortest Timehome (SHTH):

The second smart charging strategy prioritises individuals in the group with shorter spent time at home. Therefore individuals who, on average, spend less time at home are allowed to schedule their charging periods first. The idea is to cover the mileage of critical participants, who are seldom at home first. The remaining charging slots are then filled by participants that spend more time at home, which therefore have the possibility to postpone charging events. They are more flexible in comparison. The characteristics of the chosen Timehome variable are thought to take advantage of individuals that stay longer at home for the benefit of the group.

3 Results

In this section, the extensively described methodology is applied to the extracted data set from the MOP. To begin with, the results of the clustering provide valuable information about the different driving behaviors of the data set. This is followed by the results of the matching process, which utilizes the identified driving behavior to create matched groups. The last step investigates the performance of the three charging strategies in the charging simulations, in which the matched groups are compared to the randomly selected groups.

3.1 Resulting Clusters

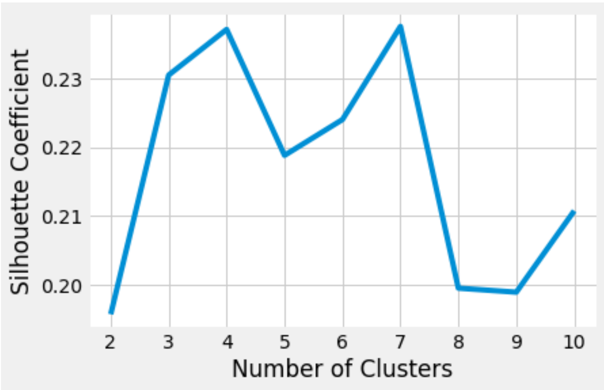

Figure 4: Silhouette Method.

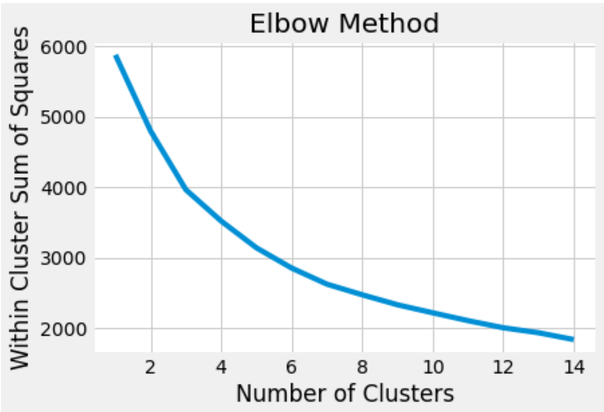

Figure 5: Elbow Method.

At the beginning of the clustering, the Silhouette Method emits similar distinction values for the fourth and seventh cluster quantities, as shown in Figure 4. This thesis aims for highly distinct driving behaviors and very similar driving behavior within the clusters, as stated in the first research question. By additionally inspecting the further decreasing Elbow Method in Figure 5, a lower distance of driving behaviors within the clusters is indicated at higher cluster quantities. Therefore the decision to choose seven clusters is logical. Additionally, this provides a more balanced distribution of households.

The normalized euclidean distances between the clusters show promisingly distinguishable results and are displayed in Table 6 on page 63. The seven identified clusters, together with their cluster centers, are shown in Table 3. Clusters with very low shares are taken into account to represent the overall inspected driving behavior. To gain a better understanding, a thorough description and interpretation of each cluster are made. The source of the description of the driving behavior is Table 3. In this table, the segmentation variables are written in italic letters. Table 7 on page 63 deals with the different professions that households from the clusters have. Further on, Table 8 on page 63 contains the specification of households from the seven clusters. These listed tables are raised by examining the linked socio-economic details about each household in the MOP. Additionally, the purpose of each driving event is also attached to the MOP and shown in Table 9 on page 64. Every cluster's driving behavior over a week is further visualized in the referenced mileage per minute diagram.

Table 3: Cluster centers of the seven 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	12.48	3.26
Timehome [h/day]	13.66	20.32	21.98	19.34	17.23	15.31	10.37
Timeelsewhere [h/day]	8.16	3.01	1.99	3.86	5.68	6.19	12.97
Roundtripcount	1.47	0.62	0.02	0.91	0.58	0.25	0.29
Tripcount	4.38	1.40	0.09	2.17	1.79	0.70	1.35
Mileagetrip [km/trip]	23.80	16.17	1.72	11.76	34.32	399.71	25.25
Start [h]	10.02	12.31	3.00	12.09	11.03	12.88	10.63
End [h]	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]	17.05	23.53	17.66	20.10	8.76	17.90	1.09
Timeelsewhere [h/day]	5.47	0.45	5.63	3.10	11.69	4.09	22.52
Roundtripcount	1.29	0.01	0.46	0.90	0.55	0.38	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	13.75	192.22	115.24	12.04
Start [h]	12.10	3.00	13.94	14.17	10.46	15.00	8.00
End [h]	15.23	7.00	15.81	15.48	17.94	11.50	16.75

3.1.1 Cluster1: high frequent commuter (medium)

Cluster1, the second-largest cluster with 28.09% of all assigned households, mainly consists of employees, visible in Table 7 on page 63. Each household is hereby classified through the profession and purpose of the trips. Additionally, this cluster contains the utmost amount of families and flat-sharing communities. Drivers of this cluster have an astonishingly high amount of trips and frequently drive home to home round trips. They are further characterised to have the second-longest trip duration and second shortest spent time at home. To be exact, they have an overall medium mileage of 23.79km on workdays and 20.21km on weekends. The purposes of weekly driving events are mainly work-related and errand-related. On weekends the driving purpose change to free-time activities or errands. A driver from this cluster is most likely to drive medium-long trips to work and tends to deal with errands on the way back home from work. On weekends these drivers enjoy their free-time activities and take care of errands. This cluster has very repetitive driving behavior, which is visualized in Figure 6. The specific peaks at the start and end of the day are most likely caused by the high amount of employees that drive during these rush-hour times to their workplace.

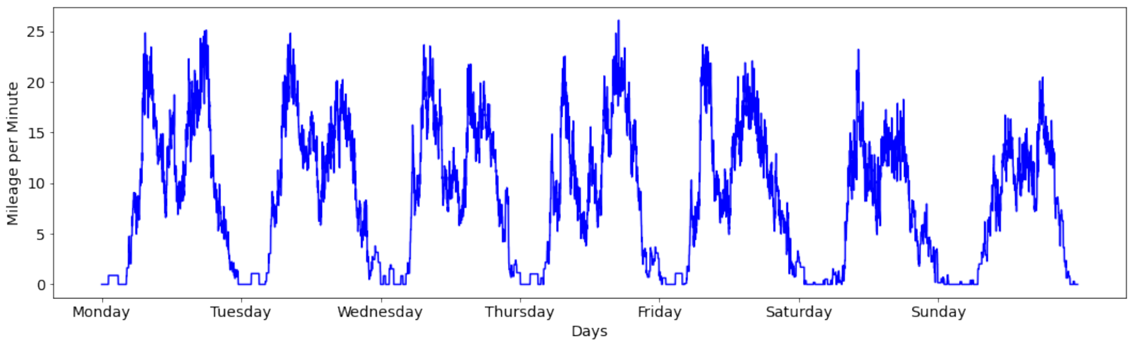

Figure 6: Daily Mileage of Cluster1.

3.1.2 Cluster2: local workday commuter (short)

16.67% of all households are assigned to this cluster, of which the majority are identified as single. The most noticeable property is the longest overall spent time at home together with the rather shorter trip duration in comparison to other clusters. In total, this cluster mainly consists of employees and retired persons who drive an average medium mileage of 16.17km on workdays coupled with the shortest mileage of only 1.18km on average during the weekend. Cluster2 contains unusual starting and ending times in their trips on weekends. Those surprisingly include a trip ending on the weekend at 3 am and starting a trip at 7 am. Through further examination, it is found that these are created by only one participant, who drives a round trip on weekends. Very few other households drive also on the weekend but do not return in the examined week. Thus, their starting and ending time is not created by the algorithm. K-means assigned such participants to the Clusters, because of other characteristics. Drivers from this cluster have a round trip at nearly every second trip, on which they go to work or arrange errands. Thus, on weekends this cluster prefers to stay at home, except for the a few driver that do not perform a round trip. The driving behavior is visualized in Figure 7.

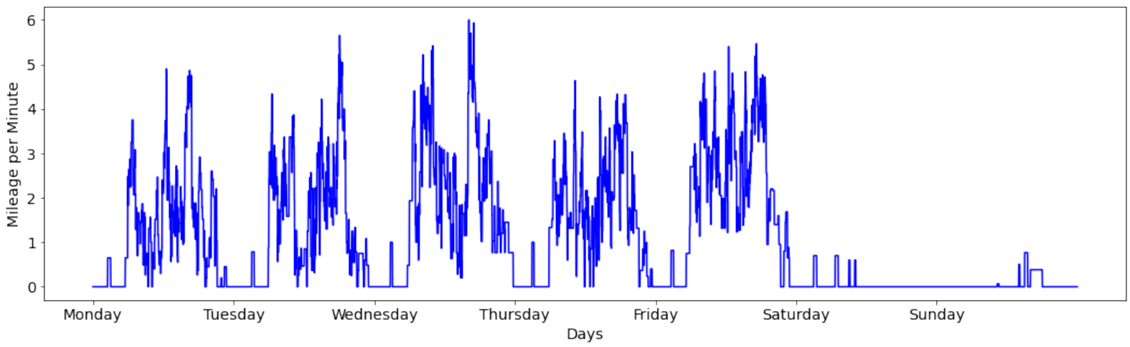

Figure 7: Daily Mileage of Cluster2.

3.1.3 Cluster3: weekend free-time trips (medium)

This cluster with a share of 7.30% belongs, therefore, to the four smaller clusters. Mainly composed of single employees and retirees, drivers from this cluster are featured with the highest spent time at home during the week alongside a relatively long time at home on the weekend. The overall trip duration is the lowest of all clusters. Driving events are preferably done on the weekend with a medium mileage of 20.76km and short trip duration. These are generally related to free-time activities. Drivers usually stay at home on workdays, which results in the cluster having the lowest trip frequency of all clusters. The driving behavior of this cluster, illustrated in Figure 8, demonstrates the opposing mirror image of Cluster2. Besides that, Cluster3 also has particular unusual starting and ending times of trips that are caused by one round trip of one driver. This cluster suffers from very few drivers that have the same issue as Cluster2.

3.1.4 Cluster4: frequent local errands (medium)

Resembling the highest participant count of 36.89%, this cluster mainly consists of employed or retired singles and couples. Moreover, the evenly distributed overall

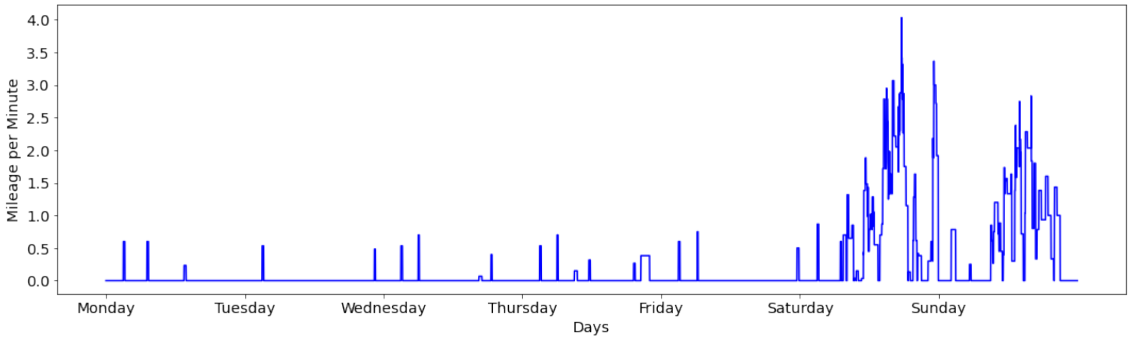

Figure 8: Daily Mileage of Cluster3.

shorter mileage and the second-highest trip frequency distinguishes this cluster from the others. Furthermore, these drivers use their cars usually for daily errands and some work-related trips. In alignment with similar visual properties like Cluster1, visible in Figure 6 on page 23, Cluster4's mileage increases on the weekend rather than decrease as the mileage of Cluster1 does. Additionally, a higher amount of errand-related trips and fewer work-related trips on workdays are prominent. This can probably be explained by the higher amount of retirees compared to employees in this cluster. This driver type has everyday errands and free-time-related trips and prefers to stay local. Similar visual characteristics like Cluster1 are shown in Figure 9.

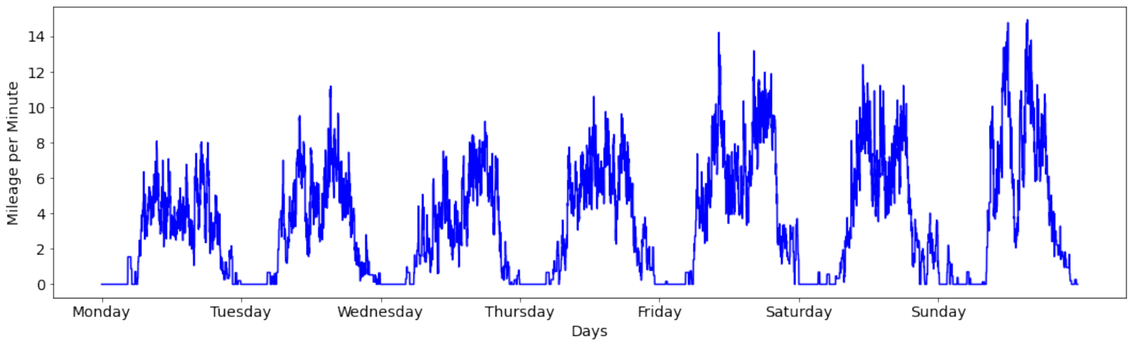

Figure 9: Daily Mileage of Cluster4.

3.1.5 Cluster5: weekend high mileage (long)

Being part of only 5.24% of all participants, these drivers spend their time at home very differently on workdays and weekends. During workdays, a medium mileage followed by a lower trip frequency describes their behavior. On weekends, the mileage drastically climbs and reaches its peak on Sunday. Intentionally, some drivers choose their second home as a destination for weekend drives, where they spend one day.

High mileage is possibly also settled by the free-time-related drives. The significant spike of mileage on weekends is illustrated in Figure 10. Furthermore, a household from this cluster uses their car for an overall mixed purpose and does not stay very local.

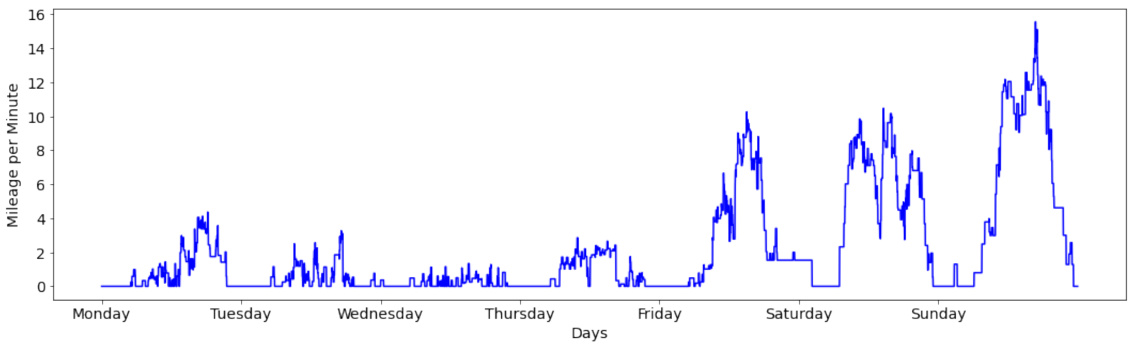

Figure 10: Daily Mileage of Cluster5.

3.1.6 Cluster6: high mileage driver (very long)

With 0.75% of all participants and a total of six persons in four households, this cluster is the smallest. Nevertheless, this cluster is essential to represent the overall driving behavior, considering their unique properties. Driving by far the highest mileage, this driver only visits 1.25 times their home during the week. This fits the most extended workday trip duration of half a day on average for these drivers. On weekends, this trend continues, hence why these drivers have the highest overall mileage per trip on workdays with 399.7km. The 0.75 round trips per weekend, together with the low time spent elsewhere, indicates that these drivers mainly spend their time in the car. The purpose of their trips is mostly free-time activities on workdays and a mixture between free-time and errand-related drives, with only one work-related driving event. The visualized characteristics are shown in Figure 11.

3.1.7 Cluster7: seldom at home (medium)

The cluster contains only 5.06% of all participants and has both individual and overall lowest time spent at home. This probably results from the three days time spent elsewhere during the week, which also is the highest of all clusters. These drivers' preferred location to stay during the week is reachable within a medium mileage, causing the drivers to make daily use of their car. The cluster itself consists of employed or retired singles and couples. Round trips on the weekend are very uncommon. Therefore, this driver type mostly drives during the week with the

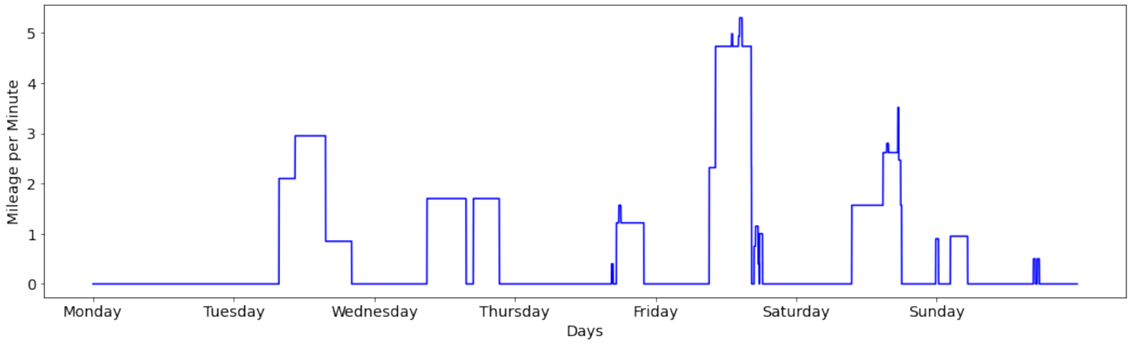

Figure 11: Daily Mileage of Cluster6.

main purpose of driving work-related trips. On the weekend, the majority of trips are errand-related, though nearly a quarter of them are used to getting to the driver's second homes. The average driving behavior is visible in Figure 12.

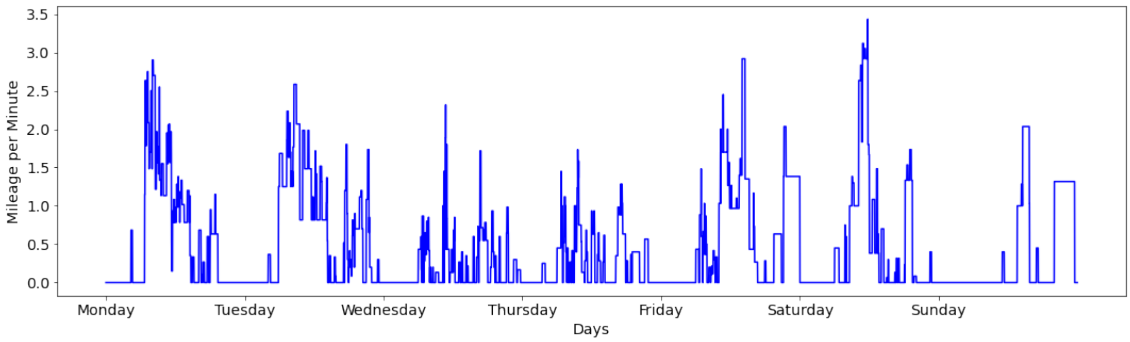

Figure 12: Daily Mileage of Cluster7.

3.1.8 Relationship and Analysis

The relationships and a short summary of unusual findings are listed in this part. The clustering resulted in interesting different driving behaviors. This leads to Cluster2 and Cluster3 that have unusual starting and ending times in their trips. These originate in both clusters from only one household that drives one round trip on the weekend in the case of Cluster2 and during workdays in the case of Cluster3. Thus clarifying the unusual starting and ending times on weekends. However, a few starting and ending times of drivers are not listed because of unfinished round trips, which the used python algorithm does not consider. By far outstanding is Cluster 6, where just four assigned households drive more than half a day on workdays and resemble the outlier of the data set.

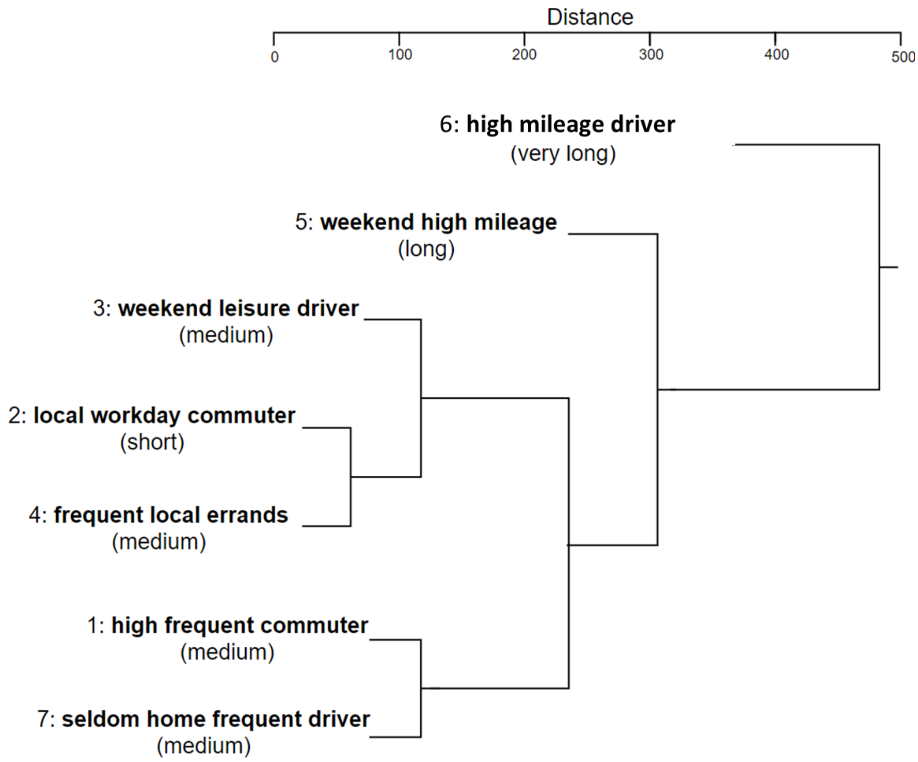

Figure 13: Dendrogram of the seven cluster centers.

The hierarchical agglomerate approach is applied to gain a better understanding of the relationship between the clusters and allows a natural interpretation of the drivers. The resulting dendrogram is shown in Figure 13. A prominent property to distinguish the cluster is the mileage, which is why the caption in brackets relates to the driven mileage. Inspecting the dendrogram further, four clusters emit from a similar group. The first pair is Cluster2 and Cluster4, which aligns with the second-lowest euclidean distance, visible in 6 on page 63. They mainly vary in the mileage and trip count on the weekend, on which Cluster2 prefers to stay at home and has nearly no driving event, while Cluster4 is far more active. The second pair consists of Cluster1 and Cluster7. They differ significantly in their trip frequency, with Cluster1 having the overall highest trip count. Moreover, Cluster7 has the overall lowest time spent at home. These two characteristics noticeably differentiate them.

Apart from the examination of the dendrogram, it is noticed that Cluster1 and Cluster4 have the lowest overall euclidean distance of their cluster centers. Both have most of their drivers allocated to them. Thus, it is expected that the majority of households have similar driving patterns in urban areas from Baden-Württemberg. This is further underlined by the second-lowest cluster distance of Cluster2 and Cluster4. However, Cluster1 and Cluster2 do not share similar driving behaviors. Examining their characteristics in detail is crucial. Visually they differ slightly through their weekend driving behavior. Cluster1's mileage decreases, while Cluster4's mileage increases over the weekend. In terms of segmentation variables, their main differences are the Tripcount and Tripduration on workdays. On workdays, Cluster1 completes twice as many trips as Cluster4 and drives more than double of Cluster4's time. In addition, Cluster1 has a much higher mileage on workdays and weekends compared to Cluster4. Other more minor differences lie in the combination of the Timehome as well as the starting and ending times. Altogether, the drivers of Cluster1 are, in average, more active than those of Cluster4.

3.2 Resulting Matched Groups

The resulting matched groups utilize beneficial relationships between cluster centers in the scope of the matching procedure's limits. The output consists of seven matched groups as a result of forcing every cluster into the matching process. The matching towards the set boundaries gives additional input on the standard deviation per matched group and is visible in Figure 14. In addition, the limit of the Timehome/Km-Ratio is assessed to obtain knowledge about their available charging time, as shown in Table 10 on page 64. The amount of each added cluster center to the matched group is translated into a percentage share and is found in Figure 20 on page 35. Each stated shares of the matched groups refer to this figure.

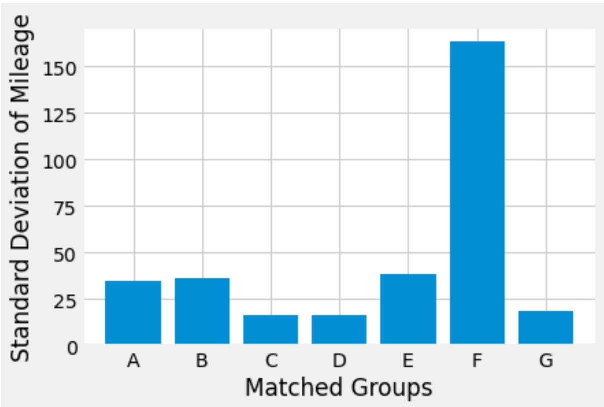

Figure 14: Standard deviation of mileage from all matched groups.

3.2.1 Matched Group A

Cluster1, with a very similar distributed daily mileage, inherits 33.3% of the shares from Matched Group A. The examined driving behavior of their cluster center is found in Figure 15 on page 31. In view of Cluster1, Cluster2 adds to the falling mileage on the weekend with a share of 13.3%. The decreasing mileage on the weekend is filled through the complementary Cluster3 and Cluster4. Both have identical proportions of 26.7% in Matched Group A. With the overall standard deviation of 34.77km/day, this matched group has a rather smooth mileage distribution. The standard deviation is created by matching this group to the possible technical limits, as mentioned in section 2.3.3. The cause for this is the interaction between all assigned clusters. In detail, the complementary properties from Cluster3 towards Cluster1 and Cluster2 are smoothing mileage on the weekend. The share of Cluster4 possibly serves to increase the overall mileage. However, the mileage from Cluster1, 2 and 4 are piling on Friday. This is why the upper limit of the matching is probably reached on Friday.

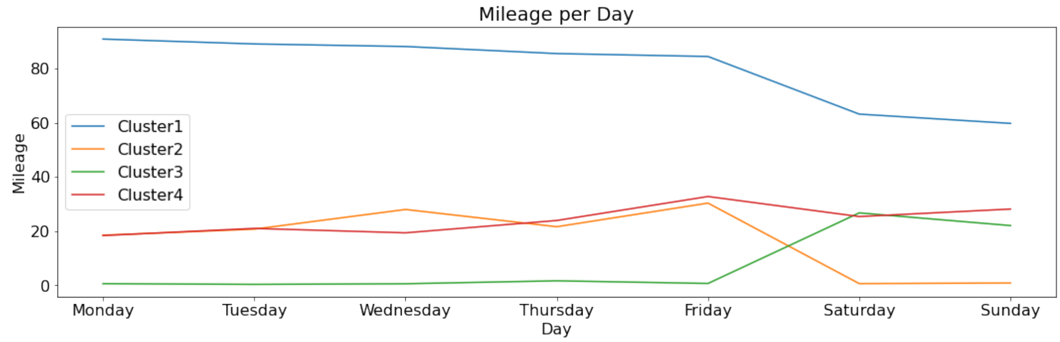

Figure 15: Daily mileage of cluster centers 1, 2, 3, 4.

3.2.2 Matched Group B

Cluster3 has the highest share of $33,3\%$ in the Matched Group B. Cluster1, and Cluster4 share the same proportion. The smallest share has Cluster2 with only 6.7%, although the matching for this group started with Cluster2. In comparison to Matched Group A, Cluster3 and Cluster2 have a higher share. From an analysis point of view, this matched group contains the identical Clusters of the Matched Group A, but the shares of the two clusters differ. These clusters are Cluster3 and Cluster2. Cluster3 has a higher share and Cluster2 a lower share in comparison with Matched Group A. The difference in these two shares probably results in the slightly higher standard deviation, visible in Table 10 on page 64, compared to Matched Group A. Nonetheless, their mean driving behavior is shown in Figure 15 and takes advantage of the known complementary properties of the allocated clusters.

3.2.3 Matched Group C

Matched Group C is equally divided between Cluster1, Cluster3, and Cluster4. This matched group uses the complementary properties of Cluster1, Cluster3, and Cluster4 that are also presented in Matched Group A and B. Figure 16 visualizes the behavior on weekends, in which the decreasing mileage from Cluster1 substitutes the increasing mileage of Cluster3. Cluster4 adds smooth mileage on top of that. These complimentary properties show their advantages on daily mileage smoothing, which is why this matched group shares the lowest standard deviation compared with other matched groups in Figure 14 on page 30. This matched group is classified to be a good match because of their overall lowest standard deviation.

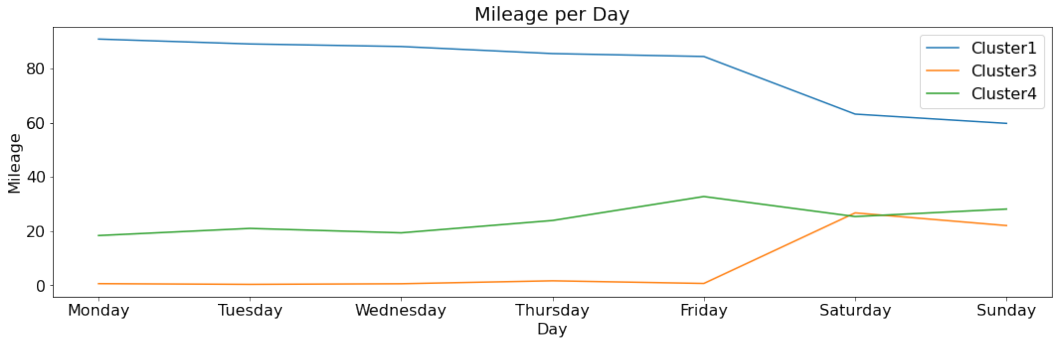

Figure 16: Daily mileage of cluster centers 1, 3, 4.

3.2.4 Matched Group D

This matched group has the identical low standard deviation of mileage like Matched Group C. In the further inspection of the Pie-Chart, Matched Group D is indistinguishable from Matched Group C. Apart from knowing that this Matched Group D started with adding Cluster4, compared to Matched Group C, no difference in their properties exist. The identical properties are visualized in Figure 16 and show that certain properties are selected more frequently by the matching process.

3.2.5 Matched Group E

Being highly distinct from other matched groups, Matched Group E has two assigned clusters. These clusters are Cluster5 and Cluster1. 85.7% of all shares are allocated to Cluster1. Cluster5 has a far-lower mileage on workdays, which start climbing on Friday. Cluster1's high mileage on workdays and the decreasing mileage after Fridays is possibly minimally contrary to the driving behavior of Cluster5. However, the high mileage of Cluster5 on the weekend is substituted by the high share of Cluster1, as illustrated in Figure 17. The adding of mileage to Friday is most likely the limiting factor. Nevertheless, the standard deviation is higher than the standard deviation of other matched groups that inherit Cluster1, 3 and 4.

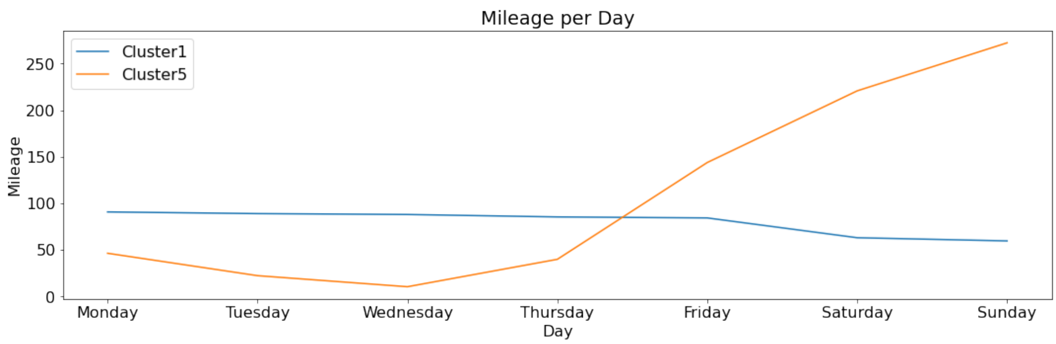

Figure 17: Daily mileage of cluster centers 1, 5.

3.2.6 Matched Group F

Most striking is the outstanding high standard deviation of 163.22km/day. This is created by including Cluster6 with a critically high standard deviation along its particular unrivaled peaks on Tuesday and Friday. No other Cluster has the specification to work complementary against these peaks. Only Cluster1 and Cluster3 are matched into this group, most likely because of their mutual complementary characteristics, which only increase the mileage until the limit on Friday are reached, as shown in Figure 18. Cluster1 has a share of 27.3% and Cluster 3 of 63.6%. Matched Group F, because of its unmatched high standard deviation, is considered the worst matched group.

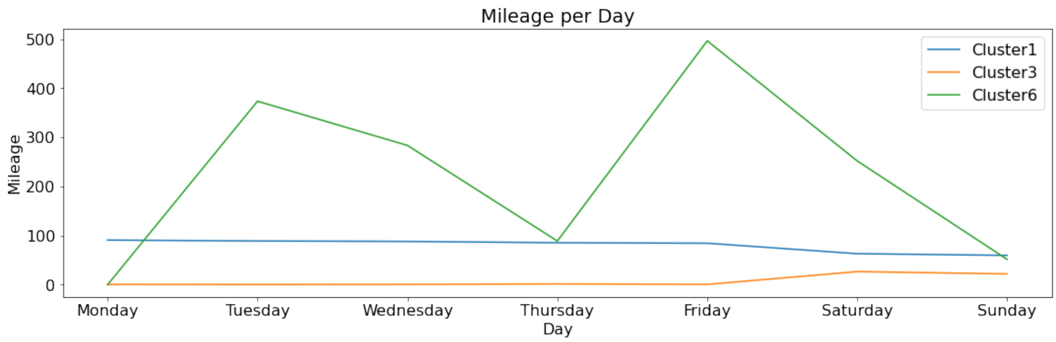

Figure 18: Daily mileage of cluster centers 1, 3, 6.

3.2.7 Matched Group G

Characterised by the second lowest standard deviation with 18.76km/day, Matched Group G makes use of the known properties from the cluster combination of Cluster1, Cluster3 and Cluster4. Except Cluster7 is added to this matched group first. Cluster7 varies more in mileage and has two smaller peaks on Tuesday and Friday. This is visible in Figure 19, compared to the other assigned clusters. This leads to the slightly higher standard deviation than Matched Group C and D. Each cluster has a share of 30.8% apart from Cluster7, which owns 7.7%. This matched group has a low standard deviation and is considered a perfect match.

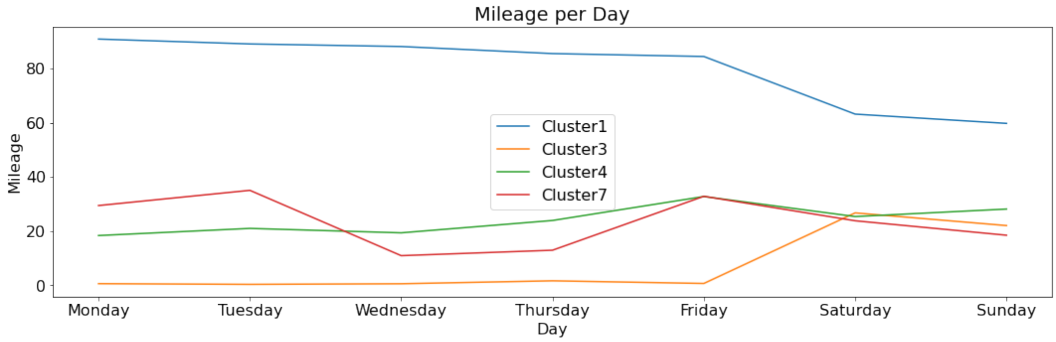

Figure 19: Daily mileage of cluster centers 1, 3, 4, 7.

3.2.8 Similarities and Analysis

Noticeably it is interesting that certain driving behaviors are far more likely to be merged together, although each cluster class was forced at least one time into the matching process. These certain driving behaviors are from Cluster1, Cluster3 and Cluster4. Their daily interaction is illustrated in Figure 16. This combination has high shares in Matched Group A, B, C, D and G, as presented in Figure 20. Nonetheless, this combination is not found in Matched Group E and Matched Group F, which have oddly shaped average daily driving patterns and inherit clusters with unrivaled high mileage. Nonetheless, the clusters that contain the majority of households, which are Cluster1 and Cluster4, are commonly matched together.

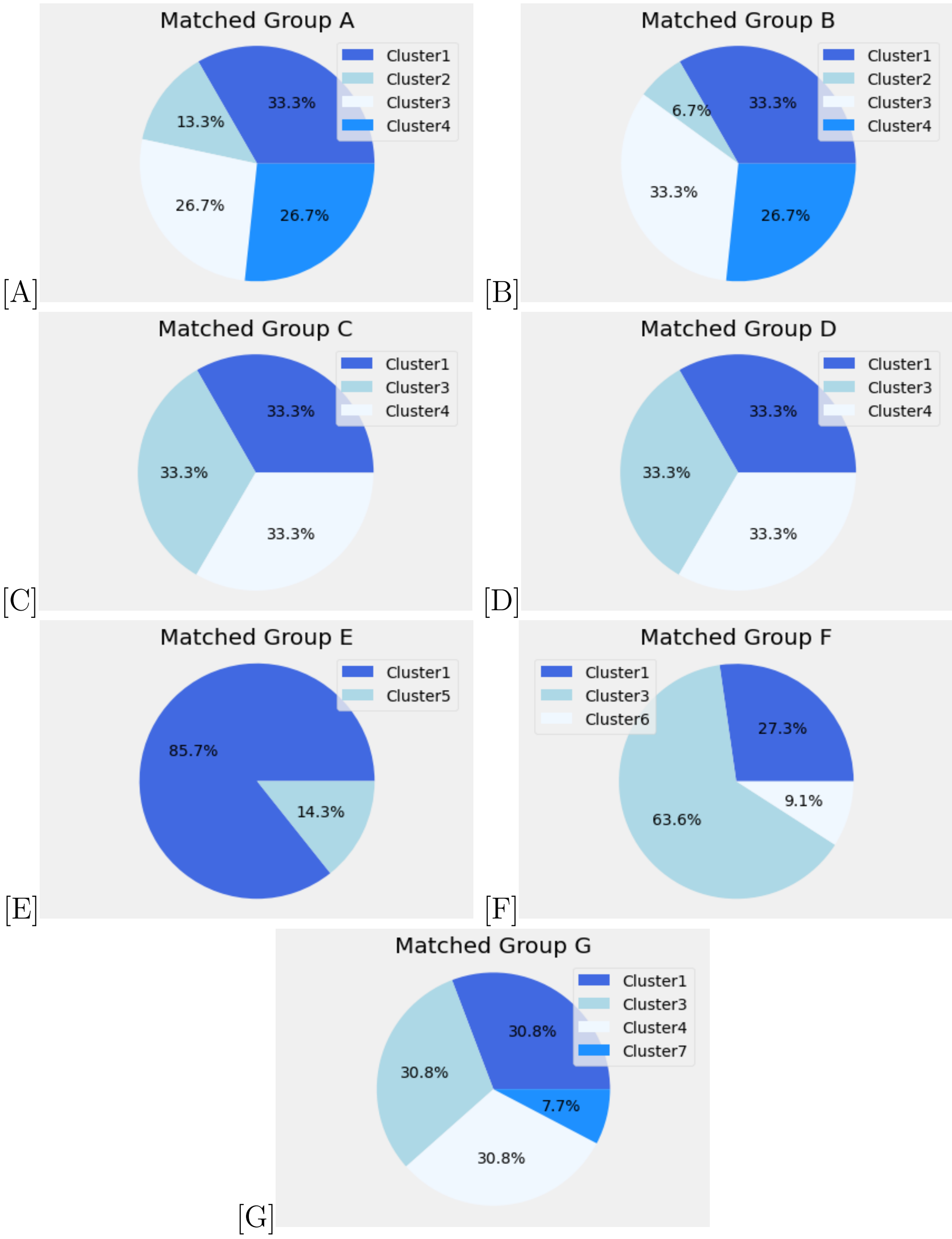

Figure 20: Pie-Charts of Matched Groups A-G.

3.3 Results of Charging Simulation

This section examines the results of the charging strategies for the two testing pools. The pool with the matched groups contains Matched Group A, Matched Group B, Matched Group C/D, Matched Group E, Matched Group F and Matched Group G. The Matched Group C and D are assessed together because of their identical characteristics. In detail, their composition is simply identical and therefore, their same shares together with their indistinguishable standard deviation have no influence on the charging strategies. The second pool contains the randomly selected participants, which were not checked for their compatibility. All created random groups are summarized by the Random Group. Hence, they represent the uninfluenced testing group.

To answer the last two research questions, the examination starts by inspecting the charging strategies of each matched group upon the different group sizes. Each group is reviewed in their covered mileage, occupancy of the wallbox and unattended switching of charging plugs for every charging strategy. The inspected charging collectives range from a minimum group size of three households to a maximum group size of fifteen households in steps of three. In the aspect of covered mileage, this thesis considers a charging strategy suitable if 90% of the driven mileage is charged at the shared wallbox, as mentioned in section 2.4.2. Hence why, charging strategies are only considered suitable above the 90%-benchmark.

The results are presented by comparing the performance of each Matched Group, illustrated in blue, against the performance of the Random Group, shown in red, in the scope of the three charging strategies.

3.3.1 Comparison of Matched Group A

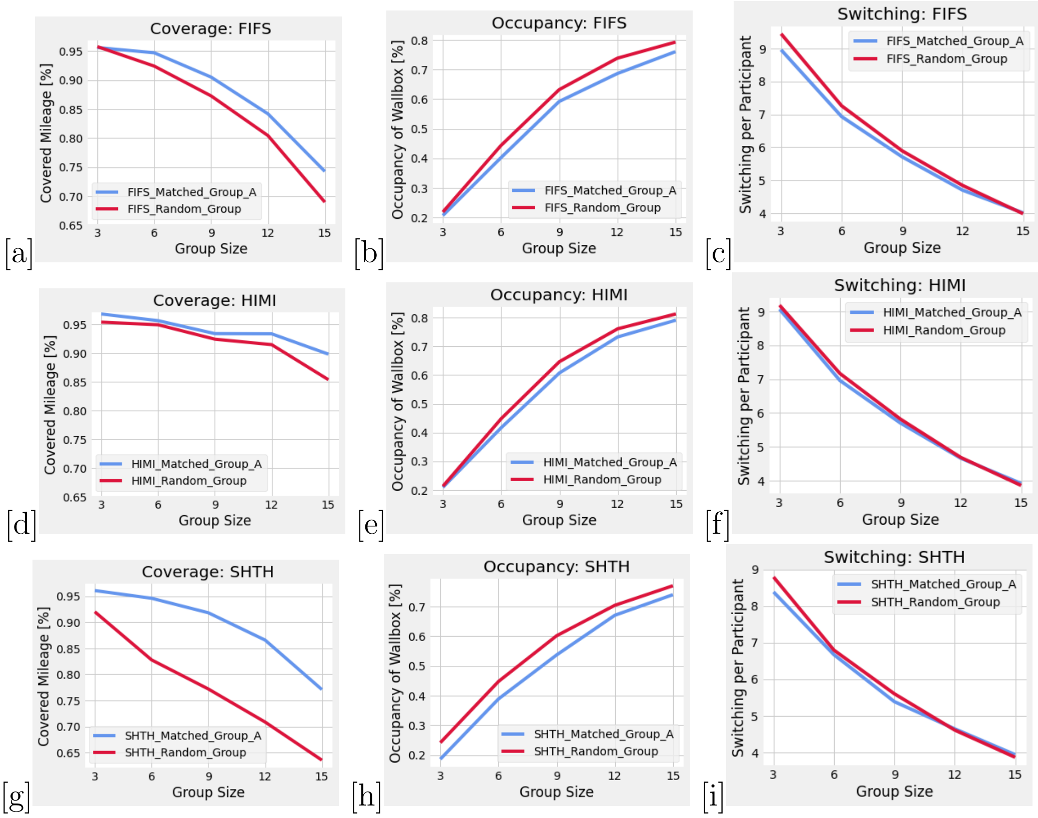

Figure 21: **Matched Group A:**
Coverage of Mileage: (a) FIFS (d) HIMI (g) SHTH;
Occupancy of the wallbox: (b) FIFS (e) HIMI (h) SHTH;
Quantity of switching plugs unattended: (c) FIFS (f) HIMI (i) SHTH.

The results of the charging strategies start with comparing the FIFS-strategy of the Matched Group A and the Random Group. All mentioned graphs are found in Figure 21. The two groups have similar starting points. At the group size of 6, they part ways, in which the Matched Group A performs better so that the 90%-mark is hit above a group size of 9 households, while the random groups fall underneath the benchmark before that at a group size between 6 and 9 households.
The HIMI-strategy results in a similar behavior until the size of 9 households at which the Matched Group A covers mileage slightly better than the Random Group. Remarkable is the identical coverage of mileage at a group size of 9. Hence why, this matched group covers mileage close to identical with 12 households assigned to one wallbox, than just 9 households. Additionally, the chosen strategy is unexpectedly able to nearly cover 90% of the car mobility needs until the group size of 15 households.
Continuing to the SHTH-strategy, a highly distinguishable progression is identified. First of all, the matched group starts clearly with higher coverage of mileage. Besides this, the Random Group falls nearly linear, while the slope of the matched

group decreases more with a climbing group size. However, the benchmark is crossed slightly later than the FIFS-strategy but far before the HIMI-strategy. Nevertheless, the Random Group performs the worst in this strategy, which is illustrated by only sufficiently covering mileage for slightly more than 3 households.

In terms of occupancy of the wallbox, each inspected strategy has nearly the same progression of their curve, in which the Random Group always has a higher occupancy than the Matched Group A. They differ only in the distance between the two curves. The smallest distance is discovered in the HIMI-strategy and is followed by the FIFS and SHTH-strategy. Occupancy means that an EV is currently plugged into the wallbox. This does not mean that the EV charges over the full minimal time slot of two hours. Thus the progression of the occupancy together with the good coverage implies that the Matched Group A uses the wallbox more efficiently than the Random Group.

The number of events for switching the plug unattended is practically identical. Only the matched group under the FIFS-strategy results starts with fewer events. Since they are very similar in the interval of 6 up to 15 households, no other distinguishable behavior is found. Both groups begin with high numbers of switching charging cables unattended, which diminishes in increasing group sizes because the charging slots exploit every free space to charge the demanded mileage, which ultimately causes seamlessly scheduled charging events. Thus an individual from this collective has to switch the charging cable to their EV up to 9 times per participant in one week at the smallest group size. Under the best performing HIMI-strategy, approximately a quantity of 4.5 switching events are discovered at the highest achievable group size above the 90%-mark.

3.3.2 Comparison of Matched Group B

Likewise, all examined results from the charging simulations are found in Figure 22 on page 39. The examination of the Matched Group B starts with comparing the FIFS-strategy. Altogether, the Matched Group B has a very similar progression like the Matched Group A, which is derived from the similar cluster center combination. In comparison to Matched Group A, the Matched Group B starts slightly better in covering mileage. At a group size of 6 households, they outperform the Random Group nearly identical.
Under the HIMI-strategy, the behavior differs towards Matched Group A. The Matched Group B does not possess a sudden fall at a group size of 9, thus it continues its trend to cover mileage better than the Random Group. However, the HIMI-strategy astonishingly manages to stay above the 90% benchmark over the whole examined interval and is the only matched group that memorably achieves to

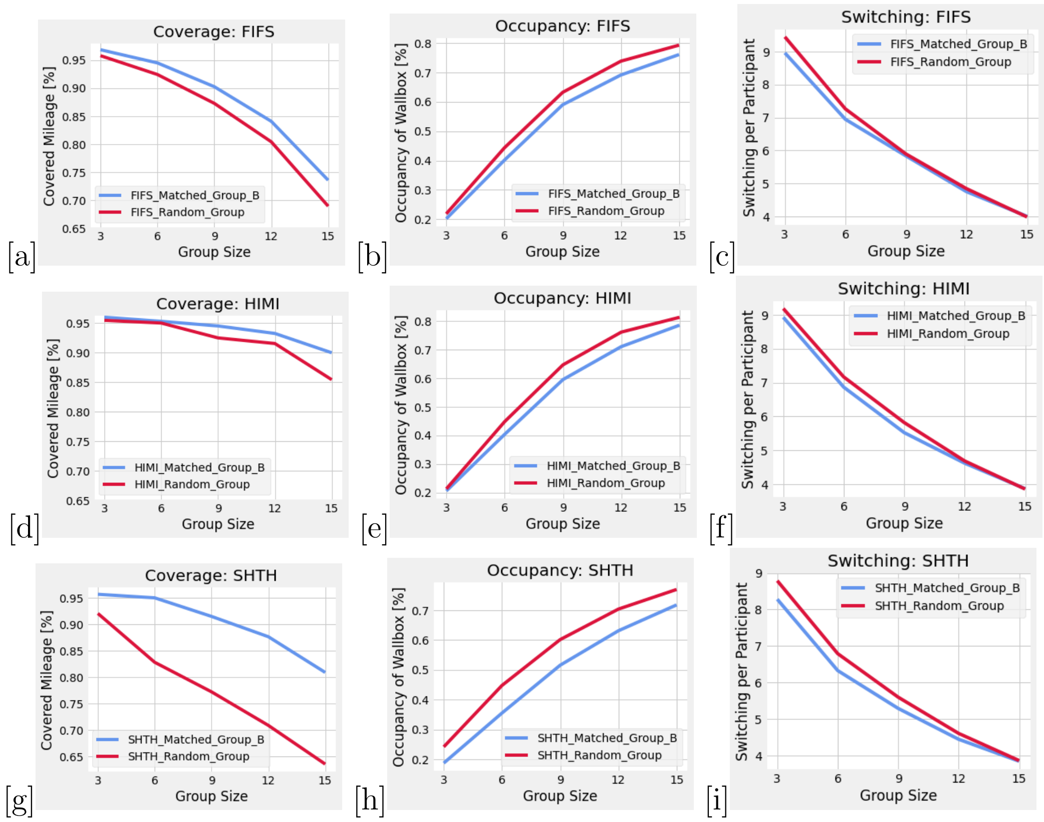

Figure 22: **Matched Group B:**
Coverage of Mileage: (a) FIFS (d) HIMI (g) SHTH;
Occupancy of the wallbox: (b) FIFS (e) HIMI (h) SHTH;
Quantity of switching plugs unattended: (c) FIFS (f) HIMI (i) SHTH.

satisfy 90% of the charging demands up to the size of the charging collective of 15 households.
Next, the same progression under the SHTH-strategy as the Matched Group A is illustrated. Hence why, also the curve of the matched group falls stronger with increasing group size. In this figure, the Matched Group B is far better than the Random Group. The Matched Group B performs under the SHTH-strategy greater, compared to the FIFS-strategy and crosses the benchmark between a group size of 9 and 12 households.

To obtain information about the charging behavior, the occupancy of the wallbox is assessed. In each strategy, the Random Group has the higher occupancy, but both have similar properties in their progressions. The occupancy differs the most in the SHTH-strategy, in which the Matched Group B has a lower occupancy. The Matched Group B utilizes the charging slots once again more efficiently than the random groups while covering mileage greater. Subsequently, the better coverage of the Matched Group B under the SHTH-strategy, together with the lower occupancy, compared to the Matched Group A, confirms that Matched Group B achieves possibly a higher efficiency. Therefore, the usage of the wallbox most likely contains the overall least idling times during the assigned charging slots.

For all events of switching plugs unattended, the Matched Group B starts lower and continues to approach the progression of the random groups. However, the Matched Group B has again nearly identical progression and only differs slightly under the SHTH-strategy. Coupling this with the covered mileage by the Matched Group B and the Rndom Group suggest a less fragmented charging scheduling alongside a more efficient usage of the wallbox. The lesser fragmented charging scheduling is derived from the unattended switching plugs. The background behind this is that seamlessly scheduled charging events always have a person that arrives at the charging stations to switch the charging cables between the car and thus, someone is present to do so. In a fragmented charging scheduling, this does not occur.
In conclusion, the Matched Group B surpasses the random groups in every aspect and achieves more efficient usage of the wallbox than the very similar structured Matched Group A.

3.3.3 Comparison of Matched Group C, D

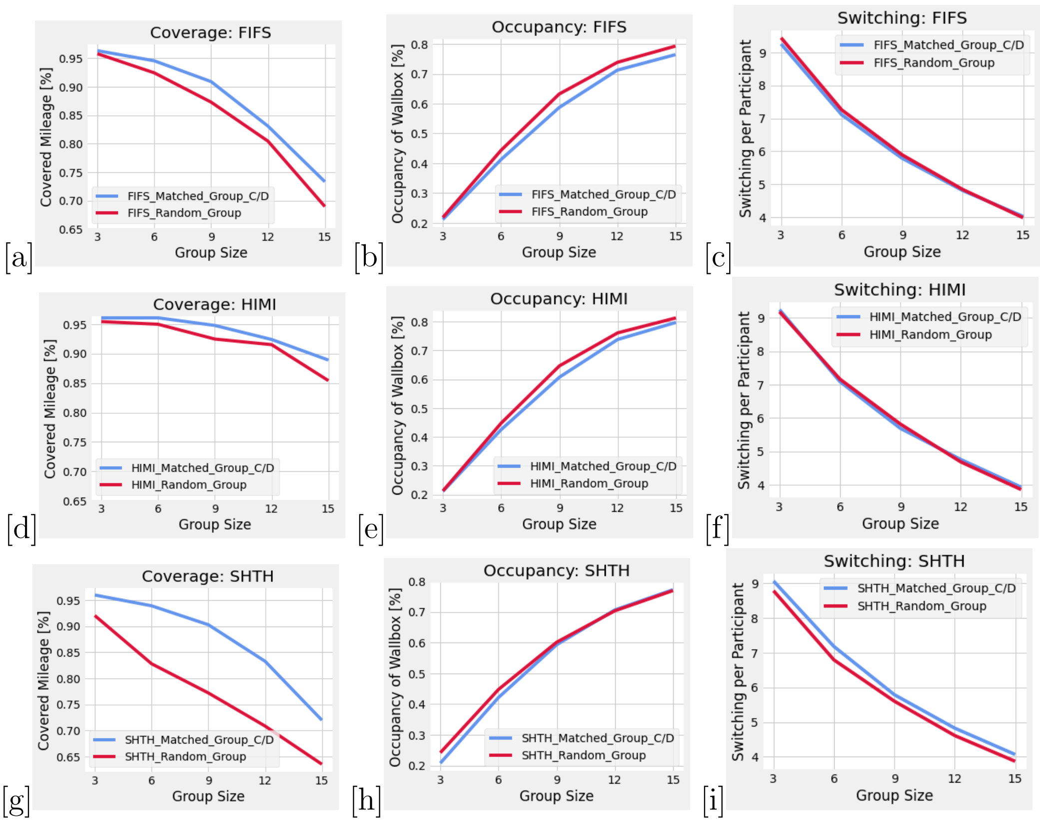

Figure 23: **Matched Group C/D:**
Coverage of Mileage: (a) FIFS (d) HIMI (g) SHTH;
Occupancy of the wallbox: (b) FIFS (e) HIMI (h) SHTH;
Quantity of switching plugs unattended: (c) FIFS (f) HIMI (i) SHTH.

The next assessed matched group is Matched Group C, which also represents the characteristics of Matched Group D, because of their identical features. Their results of the charging simulation is visible in Figure 23 on page 40. Starting with the FIFS-strategy, it is shown that the starting point of the matched group is the same as the one of the random groups. From there on, the Matched Group C and D exceeds the Random Group with very good coverage of mileage at a group size of 9. Nevertheless, the FIFS-strategy hits the benchmark after 9 assigned households. This behavior corresponds to the behavior of Matched Group A and Matched Group B.
The HIMI-strategy suits this matched group excellent in smaller group sizes. It achieves to lose no additional mileage up to a group size of 9 households and overall surpasses the Random Group. The benchmark of 90% covered mileage is hit past a group size of 12 households. In contrast to the Matched Group B, the Matched Group C does not achieve to stay above the benchmark in the inspected interval.
Further on, the trend of surpassing the random groups is also shown in the weaker SHTH-strategy, in which both groups have almost parallel degradation. Compared to the other top performing groups, Matched Group C and D are weaker in covering mileage than the superior Matched Group B and Matched Group A, but slightly better in covering mileage than the later examined Matched Group G. Apart from this, the Matched Group C and D outperform the Random Group in covering mileage significantly.

In view of the occupancy, which is shown in Figure 23 on page 40, the Matched Group C, D and the Random Group have nearly identical curve progressions. Thus it seems that all applied strategies do not work as efficiently on the Matched Groups C and D as Matched Groups A and B.

The comfort factor of switching plugs unattended is practically the same. Hence why, the Matched Group C and D have higher events than the Matched Group A and B. Only under the SHTH-strategy the Matched Group C and D result in higher events than the Random Group.

3.3.4 Comparison of Matched Group E

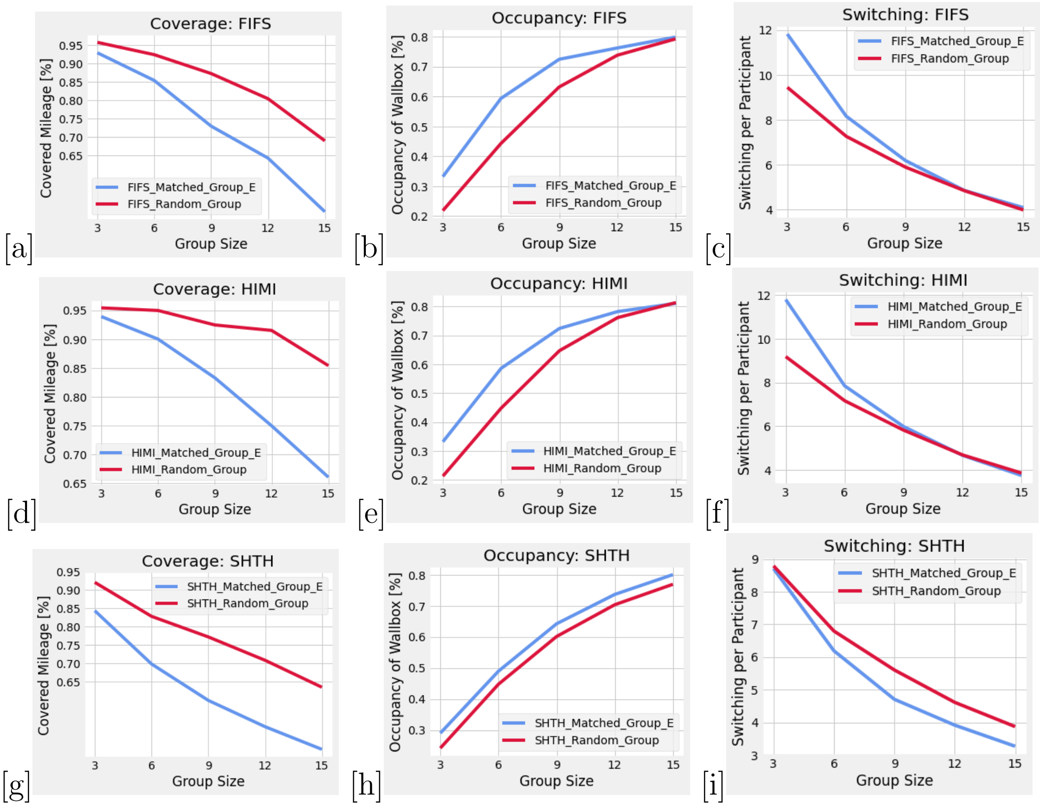

Figure 24: **Matched Group E:**
Coverage of Mileage: (a) FIFS (d) HIMI (g) SHTH;
Occupancy of the wallbox: (b) FIFS (e) HIMI (h) SHTH;
Quantity of switching plugs unattended: (c) FIFS (f) HIMI (i) SHTH.

This part starts with the assessment of the Matched Group E under the FIFS-strategy. All curve progressions of the performance indicators are found in Figure 24. The Matched Group E results by far in the worst performance and crosses the benchmark shortly after a group size of 3, then continues to fall almost linear. Therefore, the matched group stays for the whole interval underneath the better performing Random Group.
Likewise, the HIMI-strategy also shows the worst assessed performance. The Matched Group E crosses the 90%-mark at a group size of 6 households and further decreases. The next inspected SHTH-strategy is even weaker in covering mileage. The Matched Group E struggles to achieve the set benchmark at the beginning group size of 3 and suddenly decreases toward the worst documented coverage of mileage in the inspected pool. This is highly unexpected because of the similarly low standard deviation that good-performing matched groups contain.

In terms of occupancy, the Matched Group E clearly surpasses the Random Group and thus has a significantly higher occupancy of the wallbox. This is recognisable in smaller group sizes under the FIFS and HIMI-strategy and aligns with the Random

Group in larger group sizes. With keeping in mind that the Matched Group E has the overall worst coverage of mileage, the unusual high occupancy clearly indicates an inefficient usage of the wallbox. At least the SHTH-strategy shows a more alike progression of the occupancy to the random groups, which is slightly higher and proceeds side by side. Nevertheless, the wallbox is most of the time blocked and the charging collective surely is not able to cover their mileage.

Assessing the amounts of switching plugs unattended shows the highest recorded events of 12 events in smaller group sizes under the FIFS and HIMI-strategy. Only the SHTH-strategy has very few events and is settled underneath the Random Group after a group size of 3 households. Above all, the Matched Group E has a troublesome quantity for unattended switching of plugs.

3.3.5 Comparison of Matched Group F

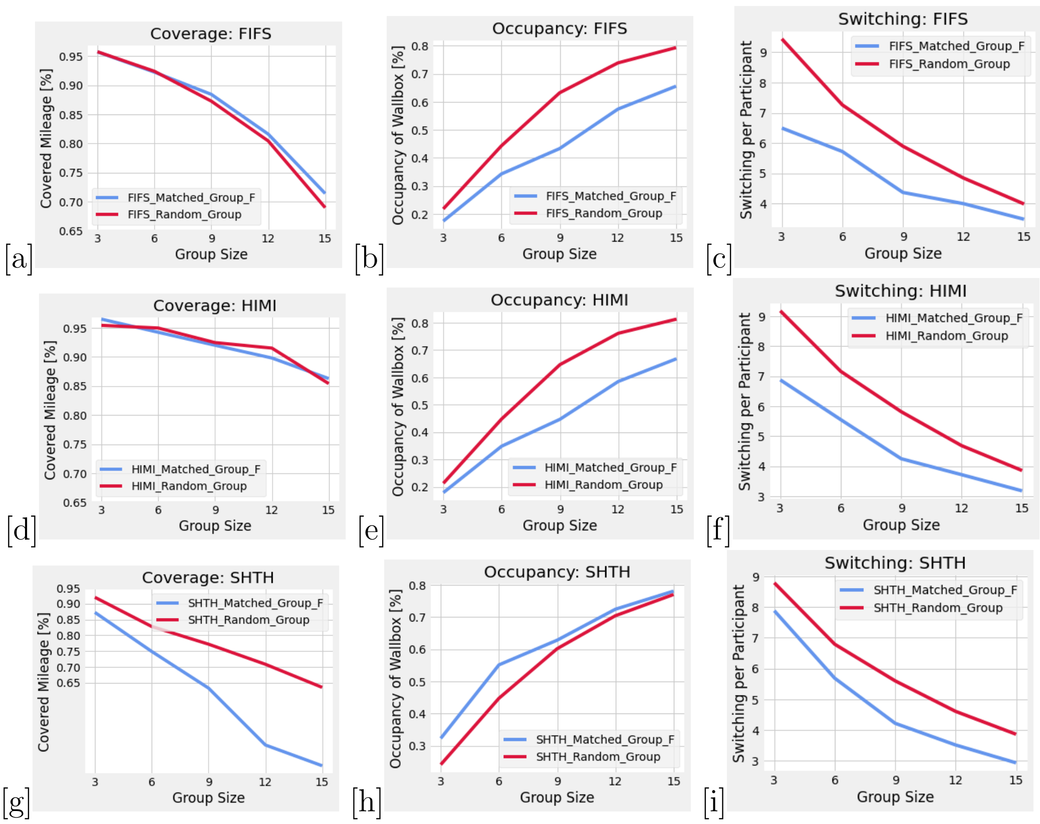

Figure 25: **Matched Group F:**
Coverage of Mileage: (a) FIFS (d) HIMI (g) SHTH;
Occupancy of the wallbox: (b) FIFS (e) HIMI (h) SHTH;
Quantity of switching plugs unattended: (c) FIFS (f) HIMI (i) SHTH.

Next is the Matched Group F. The performances of this group are presented in Figure 25 on page 43. The Matched Group F is beforehand characterised to have the by far highest standard deviation upon the matched groups. However, the curve

of the FIFS-strategy is nearly identical to the progression of the Random Group. This similar performance is further continued into the small group sizes in the HIMI-strategy. After the group size of 6, the Matched Group F slightly falls beneath the better coverage of the Random Group and they end on nearly the same coverage at a group size of 15 households.
The SHTH-strategy provides a different picture. Under this strategy the Matched Group F decreases significantly stronger than the Random Group. Above that, the Matched Group F performs slightly worse than the already under-performing Matched Group E after not even reaching the benchmark at the beginning.

The bad overall performance in charging the needed mileage is followed by an unusually low occupancy in the FIFS and HIMI-strategy, visible in Figure 25 on page 43. Nonetheless, the Matched Group is the first that achieves to exceeds the occupancy of the wallbox to this level when applying the SHTH-strategy. Besides that, it is an unexpected finding to have a low occupancy for the better performing charging strategies, while having a high occupancy of the wallbox for the worse performing charging strategy. Combining this with the knowledge about SHTH-prioritisation means that the assigned households, which have a short Timehome, block the two-hour charging slots without charging the majority of the time. On the other side, the prioritisation of the HIMI-strategy is far more efficient because Cluster6, with its high mileage, schedules charging events first.

The Matched Group F has the lowest amount of switching plugs when no one is around in all charging strategies. This effect is with lower mileage and more participants directly linked to nearly seamlessly scheduled charging slots. However, in the case of Matched Group F this probably shows the long charging events of Cluster6. Apart from this, applying the SHTH-strategy results in a slightly higher amount of events from switching plugs. The findings show that the Matched Group F is not suitable to perform better than the Random Group in covering mileage. However, the unusual low occupancy and the rather low quantity of switching the plugs unattended leaves Matched Group F to charge more efficiently than the Random Group under the FIFS-strategy and HIMI-strategy.

3.3.6 Comparison of Matched Group G

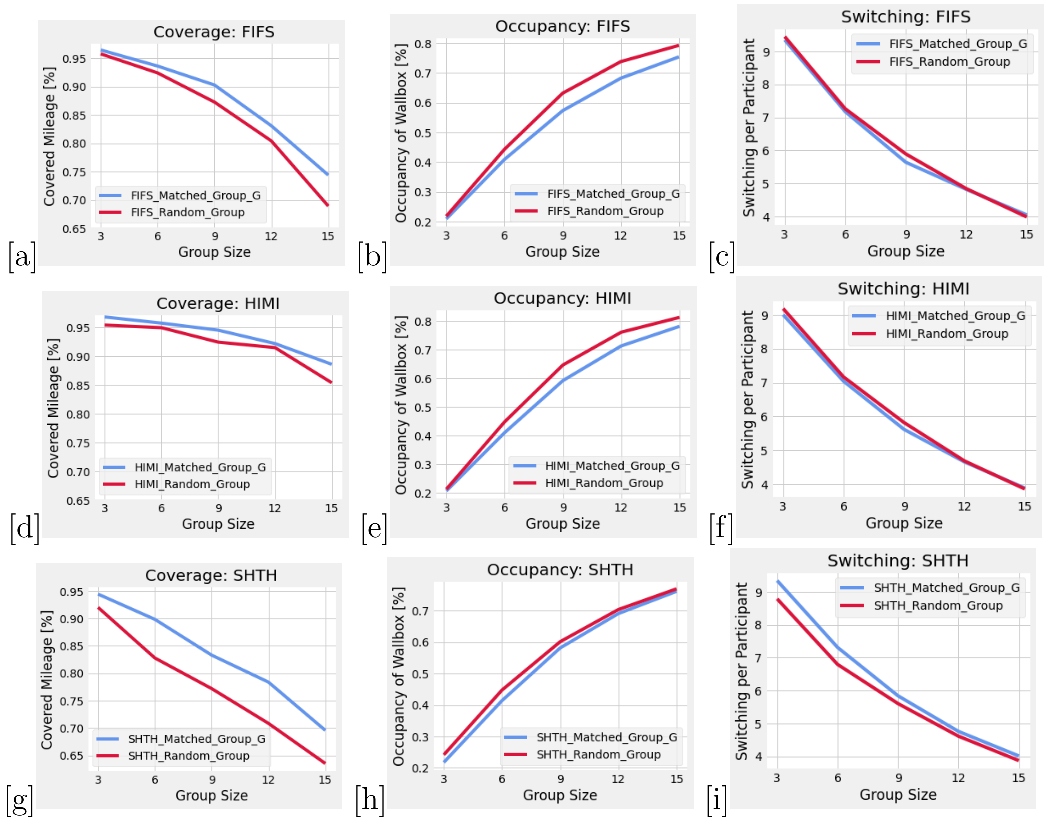

Figure 26: **Matched Group G.:**
Coverage of Mileage: (a) FIFS (d) HIMI (g) SHTH;
Occupancy of the wallbox: (b) FIFS (e) HIMI (h) SHTH;
Quantity of switching plugs unattended: (c) FIFS (f) HIMI (i) SHTH

The last examined group is Matched Group G and its progressions of the performance indicators are shown in Figure 26. The Matched Group G provides similar coverage under the FIFS-strategy as the Matched Group A and B. It also hits the benchmark shortly after a group size of 9 households. Additionally, the HIMI-strategy continues to have similar progressions to Matched Group B, but does not cover the same mileage. The Matched Group G remarkably achieves to stay above covering 90% up to a group size of 12 and crosses the benchmark between a group size of 12 and 15 households. In the scope of the SHTH-strategy, the Matched Group G stays ahead of the Random Group, but crosses the 90% benchmark at the group size of 6 households in a nearly parallel fall to the Random Group. Therefore, the Matched Group G is only better than Matched Group E and F in the SHTH-strategy.

In terms of the wallbox's occupancy, the Matched Group G stays slightly beneath the occupancy of the Random Group in every strategy. Only the FIFS and HIMI-strategy achieve to have a lower occupancy at larger group sizes. Combining this examined behavior with the generally good coverage of mileage shows a relatively efficient usage of the wallbox. Each charging slot is probably only used for charging.

The quantity for switching plugs unattended yields very similar characteristics to the curve progression of the Random Group. Besides this, the SHTH-strategy results in higher events at smaller group sizes. This indicates more fragmented charging slots.

3.3.7 Similarities and Summary

Table 4: Interval above 90%-benchmark of covering

Charging Strategies	FIFS	HIMI	SHTH
Random Group	3-6	3-12	3
Matched Group A	3-9	3-12	3-9
Matched Group B	3-9	3-15	3-9
Matched Group C, D	3-9	3-12	3-9
Matched Group E	3	3-6	0
Matched Group F	3-6	3-9	0
Matched Group G	3-9	3-12	3

In this part, the performances of the charging strategies are first summarized and then similarities in the identical intervals above the 90%-benchmark are assessed. According to methodology in section 2.4.2, the decision variables for assessing the best strategy and group are prioritised in the following order. First, the overall covered mileage is evaluated, which has the highest priority. If the values of multiple groups are quite similar, then the occupancy together with the amount of switching plugs unattended is examined. For doing so, the average values from Table 5 on page 49 are used. With that knowledge, a charging collective with a size of 3 households benefits from both the FIFS-strategy and HIMI-strategy across all groups on averages. They are very similar in their occupancy and amount of switching charging cables unattended. From this point on the HIMI-strategy dominates the remaining interval up to a size of the collective from 15 households. Altogether, the optimal strategy for large sizes of the charging collective is by far the HIMI strategy. In particular, the properties of the Matched Group B and nearly Matched Group A reach the full potential of the HIMI-strategy. The SHTH-strategy does not suit the groups that well and is by far the worst strategy. In general, high sensitivity of the matched and random groups upon the three selected charging strategies are discovered. In addition, the majority of the matched groups behave differently towards the random groups.

In the next part, the similarities are examined in the identical operating intervals above the 90%-benchmark. To provide a better comparison across the groups, this part selects identical intervals in which the groups operate above the 90% benchmark and compares the performances. The FIFS-strategy is the first strategy. The idea behind the FIFS-strategy is that uninfluenced charging behavior is monitored. Knowing this, the assessment starts. First, the superficial assessment above the 90% benchmark is taken into account in Table 4. From this, three similar groups are identified. The first is Matched Group A, B, C (respectively D) and G operate in the largest interval compared to the other groups. Examining the curve progressions leaves nearly identical progressions. They tend to have better coverage and lower amounts of switching plugs when no one is around than the Random Group. Individuals from these groups most likely have additional expenditures of up to nine unattended switching events at the smallest group size and have to switch the plug less than six times in the largest feasible group size. The second smallest interval inherits both the Matched Group F and the Random Group. Both have identical coverage of mileage in the examined interval under the FIFS-strategy. However, they differ significantly in the usage of the wallbox. In particular, the Matched Group F has a far lower occupancy besides nearly the same coverage of mileage thus charging events are more efficiently used with less idling time. In addition, the curve of switching charging cables shows way fewer events and, therefore, a higher comfort for the charging collective, in which the Matched Group F always has approximately 1-2 events less. The Matched Group F is considered to be the better group, in comparison with the Random Group, according to the methodology in section 2.4.2. The last interval above the benchmark contains Matched Group E at a group size of 3 households. Hence why, Matched Group E is very distinguishable in its curve progression from the others in the inspected FIFS-strategy and holds' the worst performance.

Next is the HIMI strategy that has a much larger operating interval above the benchmark compared to the other strategies and is displayed in Table 5 on page 49. Under this strategy the groups cover mileage the best, which is further clarified in the smallest examined distance between the curve of the Random Group and the matched groups.

From Table 4 on page46 the first assessed similar groups are constructed. In the largest interval operates Matched Group B. It is the only matched group that achieves to stay above the benchmark for the whole interval. This is why the charging collectives from Matched Group B have the remarkable ability to cover 90% of the mobility needs from 15 households that are assigned to only one wallbox. The Matched Group A is slightly behind this and falls beneath the benchmark minimally before a group size of 15 households. The second-largest interval of covering 90% of mileage belongs to the Random Group together with Matched Group A, C, D and G. In this interval performs the Matched Group A the best and its sudden fall in coverage at a group size of 9 households is not found in other matched groups. In further inspection of the curve progressions, the Matched Group C, D is very similar to Matched Group G in every aspect. Furthermore, the occupancy of the wallbox along with the amount of switching plugs is very similar in Matched Group A, C, D and G. Matched Group F is once again most closely related to the Random Group. Except for the progression of the occupancy and the amount of switching charging cables, which are very distinguishable. In both performs the Matched Group F far better than the Random Group. The smallest interval contains one more time the Matched Group E, which has no similarities in its progression to the other groups.

Furthermore, the last charging strategy is examined. Altogether, this strategy affected the characteristics of the groups the most. The SHTH-strategy achieves by dividing the groups into three groups that have different intervals, in which they cover 90% of their mileage. The most significant interval reached from a group size of 3 to a group size of 9. Nonetheless, Matched Group A, B, C, D operate in this interval without Matched Group G. The curve progressions of covering mileage are nearly identical. Only in the occupancy of the wallbox have Matched Group A and B lower values. In addition, Matched Group B has slightly lower switching events of the charging cable in smaller group sizes, which possibly roots from the higher share of Cluster3 coupled with a lower share of Cluster2. Hence why, no significant similarities apart from the covered mileage are found. This leads directly to the next interval, which the Matched Group G and the Random Group inherit at a group size of 3. Because of the better ability to charge the needed mileage from the Matched Group G, the benchmark is hit slightly before a group size of 6. Thus, the Matched Group G has similar linear curve progressions that are above the weaker Random Group. However, both groups have similar patterns in the occupancy of the wallbox and quantities of switching plugs unattended. The missing groups are Matched Group E and F, which do not achieve to cover mileage above the 90% under the examined charging strategies and are therefore not relevant for the collective.

Table 5: Averages of each charging strategy

Group Size	**3**	**6**	**9**	**12**	**15**
Coverage of Mileage					
FIFS	95.75%	92.75%	87.68%	80.47%	69.85%
HIMI	95.95%	94.76%	92.47%	89.99%	85.50%
SHTH	92.25%	85.84%	79.61%	72.11%	64.06%
Occupancy of Wallbox					
FIFS	22.08%	42.72%	58.99%	69.49%	75.65%
HIMI	22.09%	43.29%	60.32%	72.01%	78.06%
SHTH	23.61%	43.82%	58.56%	69.48%	76.32%
Switching Plugs Unattended					
FIFS	9.19	7.05	5.65	4.70	3.96
HIMI	9.17	6.95	5.54	4.57	3.79
SHTH	8.64	6.59	5.26	4.39	3.70

4 Discussion of Results

Before the interpretation of the findings starts, the main aim of this thesis is restated. This thesis assesses the feasibility of sharing a wallbox within a collective in the scope of the examined charging strategies. Understanding driving behavior through clustering was the first step. Followed by the creation of matched groups to obtain more benefits in covering mileage and efficiency for the collective. Then, charging events were simulated over a week for the randomly selected group and the matched groups in order to compare their characteristics.

4.1 Principal Findings

The interpretation begins with the principal findings of the clustering. As anticipated, the clustering methodology aligns with the results of the related literature (Sodenkamp et al., 2019). Driving behaviors are indeed strongly distinguishable, which sufficiently answers the first research question and reinforces the suitability of the unbiased Kmeans-algorithm. The strongest influence on the used methodology have the chosen segmentation variables, which need to present the most important aspect of the driving behavior. In this scope, the selected segmentation variables fulfilled the demands, although the clustering of this work used timestamps, which Sodenkamp et al. (2019) did not include in their presented methodology of clustering.

Nonetheless, the clustering resulted in seven identified clusters and classified the urban areas across Baden-Württemberg in the scope of the MOP. However, the used data set was not filtered and the unusual driving behavior of Cluster6 surfaced. In detail, Cluster6 has four assigned households, which drive more than half a day on workdays. This outlier can have the tendency to influence further results. Furthermore, these high mileages are impossible to cover by using an EV under the assumption that participants only charge at home. Hence why, these challenging drivers need to charge at public charging stations due to their long trips. The suggestion to keep these four households, which contain six drivers, could be seen as unnecessary but provides this thesis with additional knowledge of less common driving behaviors.
Another unusual finding emerges through the clustering. It is Cluster2 and Cluster3 that have extraordinary starting and ending times in their trips on weekends and workdays, caused by round trips of one household. These clusters inherit some other drivers, which drive on weekends and do not return before the end of Sunday. Hence why, no starting and ending times were assigned to these drivers by the used algorithm because they do not fulfill one round trip. Fixing this issue in the algorithm

or filtering these participants by the guess of the viewer could reduce the intracluster distances and could even generate a cluster that only drives on workdays or weekends. Moreover, Cluster1 and Cluster4 have the lowest distance between their cluster centers. In addition, the cluster centers of Cluster4 and Cluster2 have the second shortest distance. Considering that these three resemble the largest clusters, it can be expected that the majority of households have somewhat similar driving patterns across urban areas in Baden-Württemberg. With all these findings, the clustering is plausible and created a sufficient basis for this work.

To answer the last two research questions extensively, this study created a matching process on its own assessment. Smoothing mileage seems plausible to reduce peaks on a daily basis in charging demands. For doing so, the candidate is chosen, which generated the lowest joint standard deviation along with the already existing collective. A matched group is finally formed when the set technical limits are reached. In particular, it is important to understand that the ability to cover mileage of the established matched group depends strongly upon the quantity and quality of complementary driving behaviors of the data set.

The choice to only focus on the Mileage/Trip to match driving behaviors left the opportunity open to match people according to their actual arrival and departure times. However, this thesis chose the approach to step further back from such detailed matching in order to first assess whether matching is, in the first place, possible and beneficial. This approach left enough room to create very beneficial matched groups, especially for larger group sizes. Although, the cluster centers were only used. Nevertheless, in its specifications, the matching process is also applicable to individuals, which would allow matching the actual driving behavior and not only the estimated driving behavior. This is why the matching of individuals would probably result in better-performing matched groups with the same methodology. Noticeably, it is interesting that certain driving behaviors are far more likely to be merged, although each cluster class is forced into the matching process at least once. The frequently appeared combination consists of driving behavior from Cluster1, Cluster3 and Cluster4, which is called the 134-combination for now. Upon further inspection, the most compelling interpretation is that Cluster1 and Cluster3 work nearly perfectly complementary to each other. Cluster4 is added because of its seemingly low standard deviation and therefore helps to increase the overall driven mileage when Cluster1 or Cluster3 are not chosen because of a higher standard deviation. In the aspect of the visual assessment of the daily mileage, an often low standard deviation of the matched groups is present, which have high shares of the mentioned combination. One can interpret that a low standard deviation is a signal for complimentary working cluster combinations. This interpretation is further underlined by the difficult-to-match Matched Group F, whose dominant peaks, together with its unrivaled high mileage of Cluster6 cannot be compensated for in the set boundaries to reduce the standard deviation. Nonetheless, only the performance of the groups under the charging strategies can clear that interpretation up.

Although matching complementary drivers by their standard deviation works well in terms of lower standard deviation, some findings are hard to make sense of. In detail, Matched Group A started with the assignment of Cluster1 in the first selection to force every Cluster at least one time into a matched group. However, Matched Group A carries a small share of Cluster2 that was not forced into this group. This would mean that in one particular cluster combination, the addition of cluster2 provides the smallest joint standard deviation and thus smooths the overall mileage. The seemingly visual complementary characteristics of Cluster2 and Cluster3 could have been the key for that, which could root in the similarities to Cluster4 that were recorded in the assessment of the distance between the cluster centers. From looking into the other matched groups, only shares from Cluster2 are prominent in Matched Group A and Matched Group B. However, Cluster2 was only forced into Matched Group B and not into Matched Group A. Knowing these two things when interpreting this strange occurrence could only mean that the sequence in which the clusters are added to the potential collective is the cause. This interpretation could be further supported by the different shares of Cluster2 in the two matched groups (Matched Group A and Matched Group B). Cluster2 has a much smaller share in Matched Group B, although Cluster2 is assigned first to this group. This would mean that Cluster2 is potentially added in the later progression of constructing Matched Group A. Hence why, this leads to the interpretation that adding Cluster2 into the 134-combination in the later stage results in the slightly lower standard deviation of Matched Group A. In view of Matched Group C and D, which started with Cluster3 and Cluster4, no share of Cluster2 is found, probably because the dominant 134-combination starts with different clusters other than Cluster1 or Cluster2. This concludes the interpretation that the actual sequence on how a matched group is constructed influences their properties to some extent.
In addition, the other unusual finding of Matched Group G is that it has the lowest standard deviation of the matched groups. Likewise to Matched Group A and B, Cluster7 also has a minimal share next to the 134-combination within the Matched Group G, which started by assigning Cluster7 first. Consequently, this means that starting with a differently shaped driving behavior of Cluster7 and later adding the known 134-combination creates a smoother overall mileage. Thus this finding could also connect to the interpretation that the sequence in which clusters are added is of high importance.

In terms of the charging simulation, very different performances were examined.

The methodology directly influences these results. The set assumptions and boundaries heavily influence all results from the charging simulation. First of all, the set minimal charging time of two hours creates in some groups idling times, in which an EV is already recharged but remains plugged into the wallbox. This is probably more common in urban areas because of the rather short trips. Reducing this minimal charging time would create a better coverage of the wallbox, while also increasing the amount of switching charging plugs drastically and creating high traffic at the wallbox. Likewise, the switching of plugs would increase with more EVs that households possess. Thus, the assessment of the minimal charging time presents a trade-off between comfort and the availability of charging. The same trade-off is also created by the set resting time. Other factors that influence the charging are the assumed wallbox specification and the assumed EV consumption. Having a wallbox with a higher output would reduce charging times and provide the opportunity to share one wallbox within a larger charging collective. However, increasing EV consumption creates the opposite. The last influence on the performance has the smart charging strategies. Their alteration can have a big impact, which was demonstrated by the very well-performing HIMI-strategy and the bad performing SHTH-strategy. To measure these performances, the uninfluenced FIFS-strategy was used. In this regard, the prioritisation was only enforced in which unsupervised flexible scheduling took place. The advantages of such a concept are shown in the superior HIMI-strategy, but on the downside, this concept backfired with the SHTH-strategy. Subsequently, no meaningful statement can be made regarding the flexible scheduling.

Most importantly, this thesis demonstrates that establishing a shared charging collective is, indeed, possible. In particular, all matched groups exceeded the Random Group except for Matched Group E and Matched Group F. These two Matched Groups were created by forcing small clusters in the matching process. This means in context that 5.99% of all households have no characteristics that are suitable to be matched and therefore, they perform worse than a randomly selected group. However, the Matched Group F, with its high mileage drivers, has a lower occupancy along a lower amount of switching charging plugs unattended while simultaneously covering the same mileage as the Random Group under the FIFS-strategy and HIMI-strategy. Therefore, it is clarified that the matching of the majority of driving behaviors is, in fact, more advantageous and results in better coverage of mileage along with a more efficient usage of the wallbox. Additionally, hard-to-match households result in a more efficient usage of the wallbox and fewer events of switching the plug unattended, which further underlines the beneficial properties of the matching. Furthermore, a real-world implementation in the aspect of the achievable size of the charging collective could increase the financial incentive even more and it is probably worth the effort to be implemented. To answer the last research question, the Matched Group B achieved to cover 90% of their mileage up to a charging collective that contains 15 households. This astonishingly high number, along with the ability to redefine the matching algorithm, underlines the great opportunity of identifying and matching driving behaviors.

Apart from these remarkable results emerged some other unexpected findings. The first is the concerning similar driving behavior of the two largest clusters discovered in the clustering. The concerns about the two clusters, Cluster1 and Cluster4, are diminished by the extraordinary performance in their beneficial 134-combination. Thus, Cluster1 and Cluster4 do not inhibit each other. Instead they need each other to perform extraordinary with the complementary properties of Cluster3. This also applies to Cluster2, which is the third-largest cluster.

As anticipated, the matched groups resulted in different performances. It is thought that the maximal reached standard deviation in the matching process within the set limits is linked to the performance of the groups. In general, matched groups with a low standard deviation performed better. Only matched groups below a standard deviation of 36.33km inherit the superior coverage of mileage. Nonetheless, Matched Group E does not follow this plausible interpretation with its only slightly higher standard deviation of 38.61km. In addition, Matched Group E performs far worse than the expected poor performance of Matched Group F, with by far the highest standard deviation. Above all, it poorly performs and falls beneath the Random Group. Thus, the Matched Group E is by far the worst-performing matched group across all charging strategies. Finding the root of this exceptional finding is essential to understanding the relationship between a low standard deviation and good performance in the shared charging collective. First, it is essential to note the overall poor performance of the Matched Group E. Particularly, the Matched Group E under the FIFS-strategy and HIMI-strategy crossed the benchmark at a group size of 6 households, while the SHTH-strategy did not even achieve a 90% coverage of mileage. Second, the Matched Group consists exactly of two clusters. These are high frequent commuters (Cluster1) and high mileage drivers on weekends (Cluster5), in which Cluster1 takes $85,7\%$ of shares. The root of the unexplained bad performance is found in the properties of these two clusters. In the examination of those, Cluster1 has the second shortest Timehome with only a bit more than half a day for charging events. Considering the high share of Cluster1, it could be interpreted that the cause of the poor coverage of mileage roots from two causes. The first is that drivers from Cluster1 have a very short Timehome and thus simply have fewer options to charge their EVs. The second cause for this is arguably the high share of only one cluster, which on top is Cluster1 which contains high frequent commuters. Hence why, the piling of the same driving behaviors is probably the reason. In particular, the same average driving behavior results in nearly identical scheduled charging slots, which therefore create demand peaks. Altogether, the few temporal limited charging slots are additionally occupied very fast through similar arrivals times. That would also explain the remarkable high occupancy at smaller group sizes. This is obviously a weak spot of the matching algorithm, which could be improved by matching drivers individually and considering their arrival and departure times. In total, two interdependent interpretations can be drawn from the results. Hence, a low standard deviation is possibly linked to a superior coverage of mileage and more efficient use of the wallbox from the charging collective in comparison to charging collectives with a higher standard deviation, when the group's heterogeneity in their driving behavior is additionally reached to some extent.

Alongside the testing of the different matched groups, some similarities in the same charging strategy were discovered. The question arises why these similarities are often discovered in great performing groups. This leads to begin with the charging strategy FIFS, in which Matched Group A, B, C, D and G have very similar progressions. The FIFS-strategy shows the uninfluenced scheduling of charging slots according to Flath et al. (2012). Nevertheless, this would mean that these groups have nearly identical charging behaviors in their uninfluenced natural form. This possibly originates from the dominant Cluster1, Cluster3 and Cluster4 combinations that are very prominent in these groups. The minor differences in their performance are most likely linked to other smaller shares within the matched groups. Furthermore, the groups in which the 134-combination dominates have the best coverage of mileage under the FIFS-strategy. Thus it is concluded that the combination of having a high frequent commuter with medium mileage (Cluster1), a weekend leisure driver with medium mileage (Cluster3), along a frequent local errands driver (cluster4) is perhaps a superior collective. In fact, it can cover 90% of their needed mileage up to a group size of nine households under the FIFS-strategy. This finding traces the curve to the matching, in which the 134-combination is predominately created. Hence, the matching algorithm pursues the goal of having beneficially matched groups.

Other similarities in the FIFS-strategy have Matched Group F and the Random Group. They both have very similar properties in covering mileage. This would mean that Matched Group F, with its shares, resembles the randomly selected groups. Especially, a high share of a weekend leisure driver (Cluster3) alongside smaller shares of a high frequent commuter (Cluster1) and a very small share of a high mileage driver (Cluster6) represent the Random Group in covering mileage under the FIFS-strategy the best. This similarity is maybe caused by the combined characteristics of the said clusters, which are probably similar to the mean of the random groups. Nonetheless, this is not transferable to the charging behavior, in which the Matched Group F has a lower occupancy of the wallbox and a smaller quantity of switching while covering the same mileage.

It is continued with the discovered similarities in the superior HIMI-strategy. This strategy proved its worth and should be implemented. However, the actual determination of mileage in a real-world scenario needs time. Furthermore, the HIMI-strategy achieved to reach the maximum possible group size of 15 households through the Matched Group B and answered the last research question. The prioritising of individuals with a higher mileage increases their performance and the performance of all other groups. Simultaneously, some unexpected findings are present. The mentioned sudden fall in covering mileage from Matched Group A at a group size of 9 households is one of them. Besides that, Matched Group A only differs from Matched Group B in the higher share of the local workday commuter (Cluster2) and a lower share of the weekend leisure driver (Cluster3). However, it is hard to make sense of the afterward identical coverage of mileage at a group size of 12 from the Matched Group A. The only possible interpretation is that upon a group size of 12 households, the different amounts of the shares of Cluster1, 2, 3, 4 reach astonishingly a complimentary working charging collective that performs nearly identical to a charging collective with 3 households less when the HIMI-strategy is applied. This implies that unknown beneficial combined characteristics are created in the matching process through adding cluster centers one by one.

Next is the SHTH-strategy that resulted in very distinguished coverage of mileage and charging behavior across the groups. Therefore, only Matched Group A, B, C and D are somewhat alike in covering mileage. They differentiate in their occupancy of the one shared wallbox, in which Matched Group A and B have a lower overall occupancy. This could once again be linked to the interpretation that matched groups result in a better performance, which mainly consists of the 134-combination. Nonetheless, prioritising individuals by means of their time spent at home is useless for a charging strategy.

Finally, the human factor has to be considered more. It solely decides whether this proposed concept works. The matched groups within the shared charging concept might look very promising on paper. However, the identification and matching in a real-world implementation need time. It is important to note that the additional expenditure for walking multiple times per day in especially smaller group sizes to the wallbox can be unbearable for the participants. Additionally, understanding the influence of losing mileage is crucial for the further implementation of the shared charging concept.

4.2 Implications

This thesis has four major implications for practice and research. To begin with, the clustering utilized the robust Kmeans-algorithm and provided an unbiased classification of seven distinguished driving behaviors in the urban areas across Baden-Württemberg, which is evident with similar literature's methodology (Sodenkamp et al., 2019). Secondly, new ground was broken with the newly founded matching algorithm. The logical assessment of utilizing the joint standard deviation of multiple participants as a decision variable to form charging collectives is paying off, considering the overall remarkable good performance in covering mileage. Thus the work proposed a new basis for establishing matched groups. This leads to the third point that complementary driving behavior measured by the standard deviation along with a certain degree of heterogeneous driving behavior is potentially the core element to create matched groups. It contributes to the somewhat similar approach of Wang et al. (2019). This work also shows that heterogeneity in the driving behavior is a important feature for a shared charging concept in residential areas. Additionally, the utilization of complementary or heterogeneous driving behavior is also viable in the residential sector and proposes an alternative solution for residential building in the "BienVEnu Project" (Petit and Hennebel, 2019). Most importantly, the approach from Kostansek (2021) could be redefined to improve the coverage of mileage from multiple participants. The last implication addresses the crucial missing link. In literature, the assumption is used without checking the feasibility of sharing a charging station. This thesis found that sharing a wallbox within a shared charging collective is, in fact, feasible and does not significantly restrict the mobility needs of participants. Above all, 90% of the driven mileage of a charging collective is covered by one standard wallbox up to a group size of 15 households. However, the charging collective consists of specific driver types and charges under the Highest-Mileage-strategy. Therefore, this thesis's significance to elaborate a working shared charging concept contributes to the multiple found literature that utilizes shared charging concepts. The answer of the second research question mostly contributes to the business model of Azarova et al. (2020) that configuring a charging collective is possible. In particular, this work creates the possibility to split investment along with operating costs within the charging collective and thus, overcoming some economic barriers from Steinhilber et al. (2013) to make electric mobility financially attractive. Above all, diminishing technical barriers to make charging infrastructure more accessible for a broader population share in urban areas, in which increasing charging demand is most present, according to Hardinghaus et al. (2019). This thesis constitutes an excellent step towards a better understanding of driving behavior in the context of establishing shared charging concepts.

4.3 Limitations and Future Research

To finalize, this part identifies future research areas and acknowledges the occurring limitations in the presented elaboration. The most important limitations in this research are outlined. Firstly, the whole idea of sharing a wallbox within a collective only works if people are willing to do so. The high amount of manually switching the charging plugs and the minimal loss in mobility could create an intolerable obstacle. No research regarding the acceptance of such a concept was done in advance. Thus, this stays an unproven assumption. In this concern, it has not been validated in whether the examined households live nearby and can easily access the shared wallbox without additional uncomfortable expenditures for the journeys. Subsequently, one future research could be done to fill these gaps in the here presented thesis. Secondly, the data set on which all the following results are based on is subject to the assumption that the driving behavior of owners of conventional cars in fact, stays exactly the same when driving electric. In addition, driving events over one week could be considered not entirely suitable to present the mean driving behavior. These incomplete trips caused limitations in the programmed data preparation for the clustering. Future research could be done with the same methodology on larger data sets that examine EVs. Third, the matching process was limited by computing capacity. This is why the matching process is entirely based upon matching the cluster centers and not the individual drivers. Thus, the risk of uncertainty in their mean driving behavior remains present. Consequently, the same matching methodology could be implemented with more computing capacity upon driving behaviors of individuals to have presumably more beneficially matched groups. This is especially important for real-world implementation, in which the matching algorithm could be improved by checking the compatibility of arrival and departure times. Additionally, the issue of the limited computing capacity carries on into simulating the shared charging concept, which is why the group sizes were examined in steps of three households up to fifteen households and each group could only be iterated 300times. Hence why, a higher computing capacity could provide more certainty. Fourth, it is important to understand that every result of the charging simulation exists in the scope of the tested charging strategies. These charging simulations are based upon a flawless charging setup, which does not consider a loss in energy and sets a general assumption about the consumption for all EVs. Hence, it is most desirable to simulate the application of further charging strategies upon the matched groups to validate the robustness of the beneficial performance of the matched groups. Finally, the charging simulation could not inherit every consideration. In this regard, it is not proven that the established comfort factors alongside the assumed 90% benchmark for the coverage of mileage, do in fact, satisfy the charging collective in their needs. Apart from this, the charging simulation is based upon an ex-post approach, in which already driven mileage is charged. Hence, a gap in the research remains in the practicability with current technologies and in the actual orchestration of scheduling charging slots in the presented shared charging concept for a real-world implementation.

5 Conclusions and Outlook

The approach to share charging infrastructure opens exciting solution possibilities to a variety of issues. In particular, this work wants to create a beneficial charging collective for both the wallbox-container and the urban residents, which have no possibility to install a private charging station by sharing one wallbox. An additional element along the research questions is reducing costs of electric mobility by splitting investment and operating costs of charging infrastructure among a larger charging collective. The key element to fulfill these goals is the newly established matching algorithm, which detects and utilizes complementary driving behaviors.
Nonetheless, no literature was found that utilizes the standard deviation of mileage in the matching algorithm to take advantage of complementary driving behaviors in a shared charging concept. In this framework, three methodologies were applied to reach the set goals and answer the three research questions. These methodologies are the clustering, the matching and the charging simulation. The clustering answered the first research question.

- Which distinguishable driving behaviors exist in the scope of the data set?

The application of the unbiased Kmeans-algorithm identified seven driving behaviors along with providing an extensive description of their characteristics.

1. Cluster1: high frequent commuter: with medium mileage
2. Cluster2: local workday commuter: with the shortest mileage
3. Cluster3: weekend free-time trips: with medium mileage
4. Cluster4: frequent local errands: with medium mileage
5. Cluster5: weekend high mileage: with high mileage
6. Cluster6: frequent high mileage: with the highest mileage
7. Cluster7: seldom at home: with medium mileage

The matching algorithm was applied to these, which utilizes the standard deviation as a decision variable to determine the best suiting complementary partner. This generated the unexpected dominant cluster combination between Cluster1, Cluster3 and Cluster4.
Lastly, the sharing of one wallbox within the charging collective was simulated for the matched groups as well as for a randomly selected group. The groups were tested upon three charging strategies. The first strategy is the First-In-First-Served (FIFS)

strategy, which points out the unaltered charging behavior of the groups, according to Flath et al. (2012). In addition to this strategy, two smart charging strategies were applied, which rely on the sorting of individuals in one charging collective according to their properties. In detail, these are the Highest-Mileage (HIMI) strategy and the Shortest-Timehome (SHTH) strategy. Each strategy includes resting times along with factors to ensure comfort for the wallbox-container or people that live nearby. The technical feasibility of the selected charging strategies was tested. Hence, they resulted in different performance indicators upon the groups and responded to the second research question:

- Is matching of charging collectives more beneficial in terms of occupancy and covered mileage of a wallbox than randomly chosen collectives?

The identification and the matching of driving behavior proved to perform exceptionally well in covering mileage as well as having a lower occupancy of the wallbox and sometimes fewer amounts of switching charging plugs when no one is around. The combined characteristics of the described results make the matched groups considerably more advantageous than the Random Group. The combination of the outstanding coverage along with the lower occupancy results in a more efficient usage of the wallbox by the majority of the matched groups. Hence why, the scheduled charging slots possess fewer idling times and are less fragmented. Therefore, all matched groups, except for two, have the possibility to share their wallbox within larger sizes of the charging collective. Simultaneously, enhancing the possibility to split the cost between more individuals and thus reducing costs within the charging collectives. Finally, the last research question, stated below, was answered:

- To what extend can a collective of households share a charging station without influencing their daily driving behavior?

As a consequence of my research to the second question, only the predominant Matched Group B achieved to cover remarkably more than 90% mileage at a charging collective size of 15 individual households and one wallbox, under the Highest-Mileage strategy. This predominant group consists of high frequent commuters, local workday commuters, weekend free-time trips drivers and frequent local errands drivers. Nonetheless, the charging collective of 15 households covers the same percentage of mileage as a single EV with a small battery capacity and a simple private charging solution, as assessed in the research of Greaves et al. (2014).
On the basis of the researched subject, it seems fair to suggest that the potentials of shared charging concepts need further research. The human factor remains the sole decider whether the concept of sharing a charging infrastructure is possible. Particularly, the tight scheduling and the resulting high quantities of switching the

charging plug could inhibit the adoption of shared charging concepts. An intelligent wallbox with multiple charging cables that can individually charge already parked EVs could help to make sharing a wallbox more comfortable and attractive. On the economic side, the business model presented by Azarova et al. (2020) could be integrated in addition to creating a financial incentive for participation. Nevertheless, the insights provided by this work reveal that identifying driving behavior and beneficially matching them allows to gives broader access to charging stations in a straightforward approach. It shows that it is indeed advantageous to share the unused charging time of privately owned charging stations in order to provide multiple people with the opportunity to participate in electric mobility. This concept was researched in local urban areas, which suit electric mobility the best. Hence, a real-world implementation with the analyzed and matched driving behavior along with a suiting technical support system is technically viable. Future research could expand on the explanation and the origin of these beneficial properties by examining the sequence of how complementary driving behaviors are added to the matching process. As a final point, the concept of shared charging opportunities may help to further expand electric mobility and thus support the set climate goals by providing the base for future research on the technical feasibility of shared charging concepts. Hence, scientific proof is found that sharing a charging infrastructure within the presented framework is, in fact, possible and beneficial.

6 Appendix

Table 6: Normalized euclidean intercluster distances.

Cluster	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	0						
2	1.7560	0					
3	2.0292	1.7169	0				
4	1.0523	1.1636	1.4404	0			
5	1.4806	1.8035	1.8849	1.3834	0		
6	1.6122	1.8771	2.1773	1.4855	1.4360	0	
7	1.5431	1.4097	1.8041	1.3586	1.5433	1.7749	0

Table 7: Professions in the clusters.

Cluster	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**SUM**
employed	209	58	27	155	23	6	23	501
unemployed	12	6	4	15	2	0	2	41
retired	35	50	10	123	17	0	9	244
trainees	45	4	5	25	4	0	1	84

Table 8: Households in the clusters.

Cluster	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**SUM**
singles	46	61	32	91	12	2	18	262
couples	69	26	6	90	13	2	9	215
flat-sharing	10	0	0	2	2	0	0	14
families	25	2	1	14	1	0	0	43
Total	150	89	39	197	28	4	27	534

Table 9: Purpose of driving events in the clusters.

Cluster	**1**	**2**	**3**	**4**	**5**	**6**	**7**
work-related	49.42%	34.97%	70.00%	0.2649	0.3082	0.0000	0.4885
errand-related	0.3236	0.4641	0.2000	0.5144	0.3356	0.3750	0.2595
freetime-related	0.1822	0.1863	0.1000	0.2207	0.3562	0.6250	0.2519

Table 10: Timehome/km-Ratio and standard deviation of matched groups

Matched Group	**A**	**B**	**C**	**D**	**E**	**F**	**G**
Standard Deviation[km]	34.77	36.33	16.11	16.11	38.61	163.22	18.76
Timehome/km-Ratio	0.0146	0.0145	0.0154	0.0152	0.0148	0.0165	0.0164

7 Declaration

Declaration of Academic Integrity

I hereby confirm that the present thesis is solely my own work and that if any text passages or diagrams from books, papers, the Web or other sources have been copied or in any other way used, all references—including those found in electronic media—have been acknowledged and fully cited.

Karlsruhe, 29.01.2022 *Etienne Wiemann*

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