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Characterization of electric vehicle usage patterns to estimate the flexibilities and potentials for smart charging

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ABSTRACT

Electrification of passenger vehicles is an important measure to decarbonize the transport sector. An efficient introduction of electric vehicles (EVs) requires an understanding of how the charging of EVs impacts the electricity system and if, and to what extent, smart charging strategies, including vehicle to grid (V2G) services, can support the electric grid in the future energy systems. The aim of this thesis is to characterize the flexibility of smart charging including V2G by analyzing the real-world driving, parking, and charging patterns obtained from logged EVs. The analysis is based on data collected from 394 privately owned EVs and survey responses from their owners. The results reveal substantial flexibility potential for smart charging from several perspectives. However, the findings also highlight important limitations that must be carefully considered when estimating flexibility or implementing flexible charging into energy system models.

Using the lower state of charge (SOC) threshold for charging decisions and the SOC when charging ends, the flexible battery capacity range is calculated to be 59% on average. The aggregated SOC for all logged EVs is within 60%–80% throughout the entire logging period. The results show that charging is needed in fewer than half of the days in a week for more than 73% of weeks, regardless of the attributes of the EV owners, including commuter category and battery capacity. Furthermore, EVs are charged more frequently than the minimum number of charging events required per week. Thus, there is potential for charging in a way that is flexible in time depending on, for example, grid congestion or spot prices. This is particularly the case for non-commuters with large-battery EVs. The amount of time that EVs are plugged in for smart charging differs by more than a factor of two if one assumes that EVs are plugged in whenever they are parked at home and that EVs are plugged in only when they charge during the parking event. Thus, careful consideration of which of these assumptions is appropriate is essential when estimating the availability of EVs for smart charging, as the choice can significantly affect the outcomes. Installation of chargers at workplaces can increase the number of grid-connected EVs at places other than the home location, although very few EVs need to charge at workplace to fulfill their driving demand. Incentives to promote plug-in behavior at the home location can, therefore, be prove to be cost-effective at increasing the number of grid-connected EVs. This flexibility at home is exploited by EV owners with hourly electricity contracts through selecting charging times when the spot price is lower than the daily average. In this thesis, the logged EVs are clustered into three, five, and eleven clusters, resulting in groups with distinct characteristics. When the number of clusters is increased from three to five, a cluster with a low probability of parking at home during the night and a cluster maintaining a high SOC are added to the three clusters. When the number of clusters is extended to eleven, some clusters exhibit combinations of characteristics that are not present in the case with five clusters, including clusters with extreme values. Clusters with characteristics that diverge from typical commuter or non-commuter patterns are obtained.

Keywords: *electric vehicles, usage patterns, logging data, smart charging, clustering.*

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Gothenburg, May 2026
Yuki Kobayashi

List of Publications included in the thesis

This thesis is based on the following three appended papers, which are referred to in the text by their Roman numerals:

I. Y. Kobayashi, M. Taljegard, and F. Johnsson, Assessment of real-world driving patterns for electric vehicles: an on-board measurements study from Sweden, Appl. Energy, vol. 401, Dec. 2025, doi: 10.1016/j.apenergy.2025.126608.

II. Y. Kobayashi, M. Taljegard, and F. Johnsson, Characterization of passenger electric vehicle charging at different locations using real-world onboard measurements and surveys – a Swedish case study, *Submitted to Transportation Research Part D*.

III. Y. Kobayashi, M. Taljegard, and F. Johnsson, Clustering real-world electric vehicle data for flexibility of smart charging at home, *In manuscript*.

Yuki Kobayashi is the principal author of **Papers I-III** and conducted all the analyses and visualizations for these papers. Professor Filip Johnsson and Dr Maria Taljegard contributed with discussions and editing of all three papers. Dr Maria Taljegard also contributed to collections of data.

Other publications by the author not included in the thesis

Other publications by the author not included in the thesis:

A. Y. Kobayashi, M. Taljegard, and F. Johnsson, The potential for V2G logging of EV driving and charging patterns in Sweden, Conf. proceedings *37th International Electric Vehicle Symposium & Exhibition*, 2024. Seoul, Korea.

B. Y. Kobayashi, M. Taljegard, and F. Johnsson, Where do EVs charge and how long are they parked at different locations? - Logging of EV driving and charging patterns-, Conf. proceedings *38th International Electric Vehicle Symposium & Exhibition*, 2025, Göteborg, Sweden.

Table of Contents

CHAPTER 1

Introduction

As part of efforts to limit global warming in line with the Paris Agreement [1], electrification is a key measure to reduce emissions from transportation. The number of electric vehicles (EVs) is increasing worldwide [2]. In the European Union (EU), the number of battery-powered EVs reached 5.8 million in Year 2024 [3]. The number of registered battery-powered EVs in Sweden, which is the country in focus in this study, has increased dramatically during the last few years, from 9,122 in 2016 to 432,709 in Year 2025 [4], corresponding to 8.6% of the passenger car fleet in Year 2025 [4]. Moreover, the electricity system will most likely also change during the coming decade, with a larger share of variable renewable energy being used in the future [5]. Since these generation sources vary depending on weather patterns, it is important to balance the demand and supply of electricity through short response times and the ability to store electricity using, for example, batteries. When EVs are parked, their batteries may be used to shift load in time, i.e., by moving charging to low-demand hours. In addition, EVs may be adapted to discharge energy back to the grid, in so-called vehicle-to-grid (V2G) services.

Studies are needed to estimate the impact of EVs on the electric grid, as well as the potential benefits of smart charging and V2G. Energy-system models are often used to study the contributions of flexibility services from EVs to the electricity system and the grid. Furthermore, the need for charging infrastructure must be estimated for more-effective use of EVs. Such studies require knowledge of the driving and charging patterns of EVs, and they also require an understanding of the attitudes and motivation of EV owners with respect to the use of flexible charging. Until recently, there were low numbers of EVs in each region, and most passenger EVs were owned by high-income individuals who were living in larger cities, so they were not necessarily representative of the typical EV passenger fleet of a country.

Several previous studies have analyzed driving and/or charging patterns using data collected from travel surveys or diaries [6–11]. Other studies have used logged data from fossil-fueled vehicles or plug-in hybrid vehicles with small batteries to analyze driving behaviors [7,12–17]. Although some studies have logged data directly from EVs, sample sizes have typically been small [16,18–22], or limited to a few EV models or older EVs with small battery capacities, which do not reflect the diversity of the current EV market [8,23–31].

Data collected from chargers include the charging patterns of high numbers of EVs covering many models. However, such data are limited to charging events and do not include driving behaviors [32–46]. Moreover, the data collected from a high number of EVs of various types used in earlier research were often limited either temporally or geographically. Temporally constrained data are collected over a short period, preventing analyses of weekly or seasonal variations in EV usage [6,7,18,47,48]. Geographically constrained data are collected from EVs that are operating in only one or a few cities, which limits their representativeness with respect to a country's overall passenger-EV fleet [49–51]. Thus, there is a need for studies that analyze

EV usage data collected from hundreds of randomly selected EVs throughout a cross-seasonal period, using on-board GPS equipment, such that the dataset represents the entire EV fleet in a country.

Although one study has used a dataset that avoids the above limitations based on data collected in China [52], it did not include analysis of usage patterns based on the attributes of EVs, such as battery capacity or commuter category. To the best of our knowledge, there is no published study to date that jointly analyzes the perspectives of EV usage patterns in Europe:

- depending on the season and on time (i.e., between weekdays and weekend);
- at different locations for charging, such as at home chargers, public chargers and workplace chargers; and
- depending on the attributes of private EVs, such as commuter category, battery capacity, number of cars in the household and house type (i.e., apartment or detached house).

It is also of interest to analyze jointly the abovementioned perspectives of EV usage patterns.

Furthermore, energy system models are often used to study the contributions of flexibility services from EVs to the electricity system and the grid. In such models, EVs are typically treated as a single aggregated EV fleet without any consideration of individual conditions or attributes. Taljegard et al.[53] have concluded that electricity grid modeling seldom includes individual driving patterns, and that incorporating such patterns into energy system models significantly increases the number of model variables, which affects negatively the model running time and the possibilities to solve the model. Therefore, when modeling EV charging in energy systems, it is beneficial to use clusters of EVs that represent the characteristics of individual EVs. The parameters to consider when clustering include parking patterns at home, battery capacity, EV owners' preferences in relation to SOC, and energy demand for driving.

Some previous studies have clustered charging events based on the data collected from individual EVs or chargers [24,35–40]. Other studies have clustered EVs using the data collected from EVs but excluding driving or parking patterns [54,55]. Some studies have considered using driving patterns for clustering, although their clustering did not focus on smart charging [30,56] and/or battery capacity, the preferences of EV owners with respect to SOC [57]. To the best of our knowledge, no previous study has clustered EVs with the focus on charging flexibility, while at the same time considering a combination of all of the following parameters: parking patterns, total charged energy, battery capacity, and EV owners' SOC preferences.

The main aim of this thesis is to characterize the EV usage patterns related to flexibility for smart charging. An additional aim is to apply clustering to real-world EV parking and charging patterns at the home location in Sweden, and to examine the generalizability of the approach by defining the characteristics of flexibility for smart charging depending on the number of clusters.

This study uses data on driving and charging patterns for 394 randomly selected EVs distributed across Sweden. The data collection is performed using on-board GPS equipment plugged into the on-board diagnostics (OBD) port, as well as two surveys completed by the same EV owners. The dataset enables us to draw conclusions regarding the charging and driving patterns of current EVs, as well as the attributes and preferences of EV owners, using Sweden as an example. The analysis covers weekly and seasonal differences in EV usage patterns, differences that depend on location category, and differences linked to the attributes of the EVs. Furthermore, the EVs are clustered using the following parameters: parking patterns, total charged energy, battery capacity, and EV owners' SOC preferences.

This thesis is based on the three appended papers (**Papers I–III**) and this introductory essay. Chapter 2 describes the EV logging data and the surveys. In addition, Chapter 2 presents details of the parameters analyzed, as well as the applied clustering method. Chapter 3 shows the main findings and discusses them. Chapter 4 presents the main conclusions, and future topics for research are proposed in Chapter 5.

CHAPTER 2

Data and Method

Four key factors related to flexibility for smart charging are analyzed based on the EV logging data and survey responses, in this thesis and in the three appended papers. The four key factors are: EV owners' SOC preferences; energy demand for driving; availability with regards to shifting the charging time; and the battery capacities of the EVs. This thesis and the papers examine these key factors through: (i) the flexibility for smart charging during parking events with charging at each location category; (ii) the utilization of flexibility for smart charging at home; and (iii) the clustering of EVs. In this chapter, the EV logging data and survey responses are described (Section 2.1). Important parameters are thereafter defined (Section 2.2), followed by an explanation of the method used for clustering the EVs (Section 2.3).

2.1 Logging data and surveys

The driving and charging patterns of 394 privately owned, pure battery EVs were logged using an on-board Geotab GO GPS-based device [58]. **Paper I** describes the details of the dataset; therefore, the description is summarized in this chapter. The EVs represent 382 owners, since 12 of the original EV owners changed EVs during the logging period. The EVs were selected by Statistics Sweden (SCB) from all pure battery EVs registered in Sweden, excluding a few models due to technical limitations. The selection of participants was performed using stratified sampling so that the EV owners are representative of regional variations in population density (large city, small city, countryside) and housing type (detached house, apartment).

Figure 1 shows how the number of logged EVs is distributed across the logging period (**Figure 1a**) and the number of logged days per EV in descending order (**Figure 1b**). The logging period was from October 2022 to March 2025, although most of the EVs were logged in Year 2023, as shown in **Figure 1a**. As can be seen from **Figure 1b**, the number of logging days per EV spans from 5 to 786 days, with around 400 days per EV being the most common. For more details on the selection of participants, see **Paper I**.

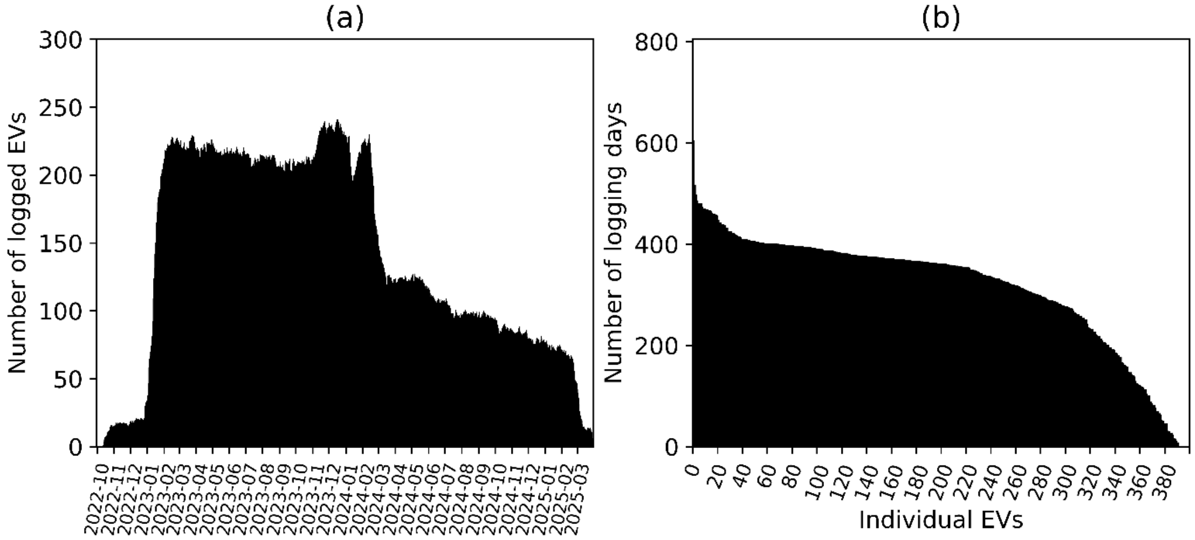

Figure 1. Number of logged EVs on different days during the logging period (a) and number of logged days per EV plotted in descending order (b). Source: based on Paper II.

The Geotab GO unit records data from the Controller Area Network through the OBD port and transmits the data to a database provided by Geotab. The Geotab database consists mainly of trip data and status data. Trip data are the events that are recorded when each trip ends. A trip event is defined as the period during which the EV is not parked. Parking is defined as the period when the “ignition” is turned off or when the driving speed remains at 0 km/h for more than 200 seconds.

The status data include the times of the start and end of charging, with the charging type distinguished as alternating current (AC) or direct current (DC), the SOC of the EV batteries, the odometer readings, the energy charged to the battery (accumulated value), and the charging power. SOC is recorded for every 0.5% or 1% change in battery capacity and the odometer readings are recorded every 1–10 km depending on the EV model. The energy charged to the battery (accumulated value) and charging power to the battery are recorded using the Ramer-Douglas-Peucker algorithm [59].

In addition to the logging data, two surveys were sent out to the participants. The initial survey (56 questions) was answered by the EV owners before the logging period started, and the follow-up survey (51 questions) was answered by the EV owners at the end of the logging period. The aim of the surveys was, among other things, to capture the EV owners’ preferences, so as to understand the reasons for their driving and charging patterns. Furthermore, the battery capacity data corresponded to the nominal battery capacity provided by the EV Database [60]. Day-ahead electricity spot prices in Sweden were obtained from the ENTSO-E Transparency Platform [61].

Parking location categories in this study include: *Home*, *Workplace*, *Vacation house* and *Other location*. The locations are defined using logging data, survey responses, and addresses of the EV owner’s residence provided by SCB. For details of the definitions of the parking locations, the reader is directed to **Paper II**. The charger categories used are: *Private home AC charger, Private workplace AC charger, Private vacation house AC charger, Other private AC charger,* *Private DC charger, Public AC charger* and *Public DC charger*. Private charger means a privately used charger, while Public charger means a publicly available charger in this study. Private chargers are defined at each parking location category (home, workplace, vacation house, and other location). Public chargers are defined as chargers that are located less than 50 m from a public charging point. The coordinates of 8,683 public charging stations with 58,319 charging ports in Sweden are provided by NOBIL [62]. Public chargers at home, workplaces and vacation houses are classified as public chargers.

2.2 Definition of parameters

The technical limitation of smart charging is, of course, the full battery capacity. However, EV owners are generally advised to keep the SOC within a certain range (e.g., 20%–90%), in order to limit battery degradation. In addition, EV owners have personal preferences regarding their SOC range. In this thesis, the preferred SOC range is estimated for each individual EV owner by calculating the lower SOC threshold for charging decisions and the most-frequent SOC reached at the end of charging. The lower SOC threshold for charging decisions better represents the preferred SOC than does the minimum SOC at the start of charging. This is because the minimum SOC at the start of charging often reflects the result of long-distance driving rather than the EV owner's actual preference, i.e., the EV owners would have charged earlier if they had access to a charger.

The lower SOC threshold for charging decisions is calculated by curve-fitting to the linear relationship between charging probability and SOC when arriving at the home location. **Figure 2** illustrates the charging probability as a function of SOC when arriving home for one EV, as an example. The charging probability is calculated for every 5% SOC interval, e.g., the value at 12.5% SOC represents the charging probability when SOC is in the range of 10%–15% when arriving home. Parking events shorter than the shortest parking events with charging of the EV are excluded, so as to focus on parking events that are sufficiently long for the EV owners to make a choice about whether or not to charge. The orange line in **Figure 2** is a fitted curve formulated as a piecewise function: the charging probability is 100% below x_1 and the charging probability is 0% above x_2. Then, it is assumed that there is a linear decrease from 100% to 0% between x_1 and x_2. For 70% of the EVs, the piecewise function achieves an R-square value of 0.5 or higher. The value x_1 is defined as the lower SOC threshold for charging decisions, since the charging probability is estimated to be 100% below x_1. If the SOC is lower than the lower SOC threshold for charging decisions when arriving home, the EV is always charged. If the SOC is higher, charging may or may not occur depending on the occasion, i.e., the decision to charge is flexible.

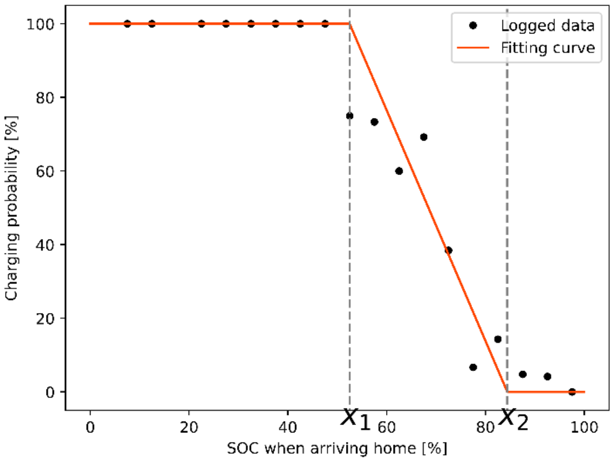

Figure 2. Charging probability in relation to the state of charge (SOC) when arriving at the home location and the fitted curve for one EV as an example. The probability is calculated for every 5% of SOC. For example, the value at 12.5% SOC is the charging probability when SOC is in the range of 10%–15% when arriving at the home location. x_1 and x_2 show the lower and upper breakpoints of the fitted curve. Source: based on Paper III.

For EVs that have a parking location other than the home location, where charging occurs more frequently than at the home location, the location with the highest charging frequency is used for the calculation, instead of the home location. This ensures that a sufficiently high number of parking events is sampled at the location where the EV is most commonly charged. Some EVs visit such locations solely for the purpose of charging, which naturally results in a charging probability of 100% for any SOC. In such cases, the highest SOC when the EV arrives at the charging location is defined as the lower SOC threshold for charging decisions, since the EV owner chooses to charge at that SOC.

EVs can be available for smart charging and V2G, if they are connected to the electricity grid. The maximum availability for smart charging occurs when EVs are plugged in every time they are parked at any location. However, in the current situation, EVs have limited access to chargers at certain parking locations, and the plug-in patterns reflect individual habits. The differences in the availability of EVs for smart charging under various assumptions are investigated in this thesis. Two cases regarding the availability of EVs for smart charging are defined as follows.

- Case 1: EVs are assumed to have access to a charger at any parking location and to be plugged in every time they are parked. The availability of EVs for smart charging is represented by the probability that a parking event occurs.
- Case 2: EVs are assumed to have access to a charger at any parking location but are plugged in only when a charging actually occurs during the parking event. The availability of EVs for smart charging is represented by the probability that a parking event with charging occurs.

Since the logging datasets contain no information of plug-in or plug-out timepoints, we assume that the EVs are plugged in and out at the beginning and end of the parking events. There may be instances where the EVs are plugged in some time after arrival, e.g., when the owner forgets to plug in, or unplugs before departure (such as when the charger is needed by another EV).

2.3 Clustering

When energy systems are modeled with flexibility of charging to (and discharging from) EVs, the EV fleet is often regarded as a single large aggregated battery. This is because implementing each individual EV into large energy system models makes the computational burden excessive. However, Taljegard et al.[53] have shown that treating all EVs as a single aggregated battery leads to an overestimation of the charging and discharging flexibilities in energy system simulations. Therefore, when modeling EV charging in energy systems, it is advantageous to use clusters of EVs that represent the characteristics of the individual vehicles.

A total of 262 EVs that recorded more than 8 months of data, without critical missing values, are clustered to examine the generalizability of the characteristics of EVs relevant to smart charging. Four parameters, representing the key factors for smart charging, are used as inputs to the clustering: (i) the probability that a parking event occurs at home at each hour and each day type; (ii) the energy demand for driving; (iii) EV owners' SOC preferences; and (iv) battery capacity. The EVs are clustered using the K-means method [63].

Since the input parameters have different units, they need to be standardized so that each parameter is assigned an equal weight. As the probability that a parking event occurs at home consists of 48 parameters [24 hours × 2 day types (weekday and weekend)], these parameters are scaled so that the Euclidean distance between EVs for this probability measure ranges from 0 to 1. All other parameters are scaled to a range between 0 and 1.

The number of clusters is determined using two indicators: the silhouette score [64] (**Figure 3a**); and the number of EVs in the smallest cluster (**Figure 3b**). The silhouette score indicates how compact the EVs are within each cluster and how well separated the clusters are from one another. Thus, a higher silhouette score reflects better-defined and more-distinct clusters. Cluster solutions that result in a low number of EVs in a cluster are avoided, as the characteristics of clusters with a low number of EVs may represent an outlier, and the results are possibly less-robust.

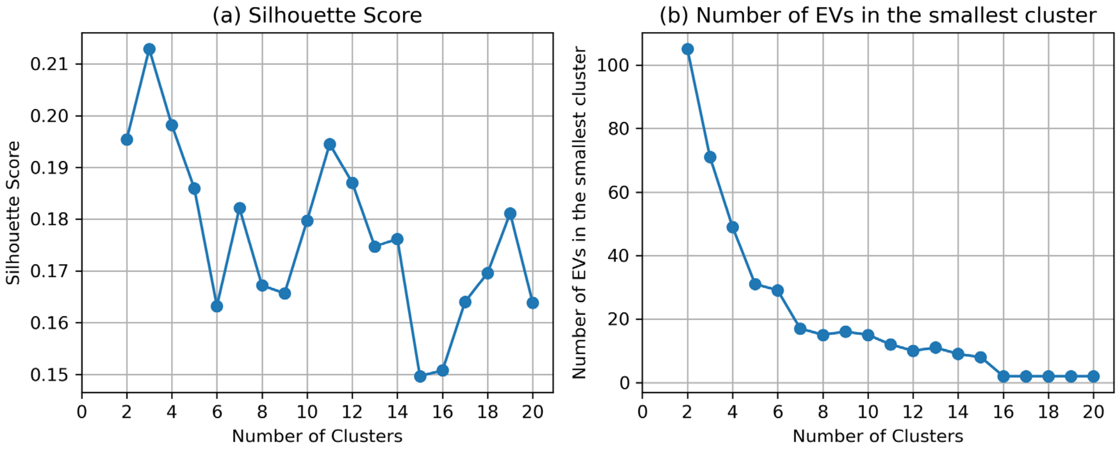

Figure 3. Silhouette scores (a) and numbers of EVs in the smallest cluster (b) depending on number of clusters. Source: based on Paper III.

CHAPTER 3

Main findings and Discussion

The characteristics of EVs that are relevant to smart charging, such as SOC, energy demand for driving, battery capacity and availability for smart charging, are often simplified when used in energy systems modeling. However, an accurate estimation must be based on real-world EV usage patterns, in order to avoid underestimation or overestimation. Therefore, this chapter presents the results of analyzing key characteristics, including EV owners' SOC preferences, energy demand for driving, availability for shifting charging time, and battery capacity, based on the EV logging data and survey responses. Furthermore, important aspects, such as the potential expansion of flexibility for smart charging in the future, are discussed. At the end of this chapter, the EVs are clustered into different numbers of groups to enable effective implementation of real-world EV usage characteristics in energy systems models.

3.1 Key parameters in relation to SOC for smart charging

The battery capacity can be viewed as the theoretically available maximum range of an EV. However, this range is not always utilized due to several factors, such as EV owner's behavioral aspects, range anxiety, limitations related to the charging infrastructure, and battery degradation. **Figure 4** shows three important SOC-related parameters that determine the potential for smart charging. **Figure 4a** shows the lower SOC threshold for charging decisions (for the definition, see Section 2.2). The lower SOC threshold for charging decisions is commonly observed between 10% and 40%. However, this value varies widely among individual EVs. For example, the lower SOC threshold for charging decisions is 50% or higher for 19% of EVs, which means that these EVs are charged even when parked with a relatively high SOC.

Figure 4b shows the most frequently observed SOC for each EV at the end of a parking event during which charging occurs and ends at the latest 10 minutes before departure. 68% of EVs are typically charged to 100% SOC if time allows. In addition, 18% of EV owners usually stop charging at 80% SOC, and 11% stop at 90% SOC. Among those who usually stop charging before reaching 100%, 88% have charged to 100% at least once during the logging period. This implies that these EV owners intentionally avoid charging to 100%, probably so as to mitigate battery degradation. Indeed, according to the survey responses, 89% of those who stop charging before 100% do so to avoid battery degradation. **Paper II** shows that large-battery EVs tend to stop charging before reaching 100% SOC, implying that large-battery EVs not only extend their driving range but also enable owners to avoid full charging, thereby avoiding battery degradation.

Figure 4c shows the aggregated SOC at each hour of the logging period when all EVs are regarded as a single aggregated battery. At the aggregated battery fleet level, the aggregated SOC remains within the range of 60%–80% throughout the logging period, as shown in **Figure 4c**. This reflects the combined effect of EV owners' preferred lower and upper SOC limits.

Paper I also shows that the SOC when arriving home for overnight parking is widely distributed, though the most-frequent SOC is 70%–80% regardless of battery capacity. Thus, while individual EVs may have SOC levels outside the aggregated SOC range of 60%–80%, the most-common SOC is within this range.

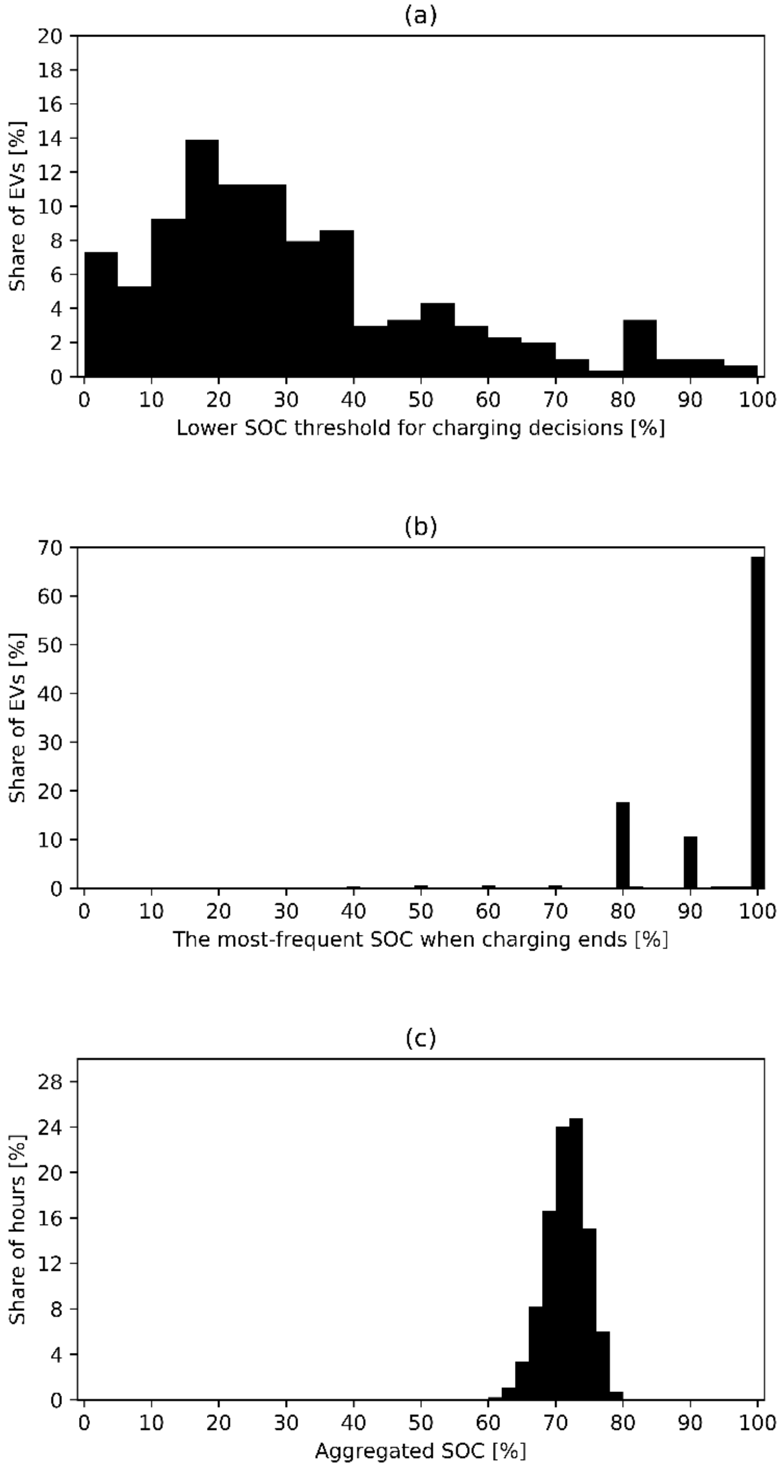

Figure 4. (a) The lower state of charge (SOC) threshold for charging decisions for each EV. (b) The most-frequent SOC when charging ends for each EV. (c) The aggregated SOC for all EVs together for each hour of the logging period.

The difference between the most-frequent SOC at the end of charging during the logging period and the lower SOC threshold for charging decisions is defined as the *flexible SOC range* of the EV. The *flexible battery capacity range* is then defined as the flexible SOC range multiplied by the battery capacity and divided by 100. Thus, the flexible battery capacity range represents the fraction of the battery capacity that is available for flexibility of charging. **Figure 5** shows the distribution of the flexible battery capacity range.

The flexible battery capacity range varies from 0 kWh to 70 kWh (**Figure 5**). The average flexible battery capacity range is 34 kWh, while the average battery capacity is 57 kWh. This indicates that on average 59% of the battery capacity is available for flexibility of charging. Although larger-battery EVs can naturally have larger flexible capacity, the spread is wide across all battery sizes. For example, 11 logged EVs with battery capacities larger than 67 kWh exhibit flexible battery capacity ranges of ≤20 kWh.

These results show that the flexible battery capacity range differs substantially between EVs depending on owner preferences and charging habits, whereas energy systems models often assume a simplified flexible battery capacity range (e.g., 10%–90% of battery capacity). Although the average flexible SOC is 59%, the aggregated SOC remains within a 20-percentage-point band (60%–80%) under current usage patterns. This suggests that the aggregated SOC range could be expanded if charging activities were more actively controlled. However, implementing such control would require incentives and/or systems capable of coordinating charging across different EVs. To avoid overestimating the level of flexibility, the flexible battery capacity range for each individual EV must be taken into account.

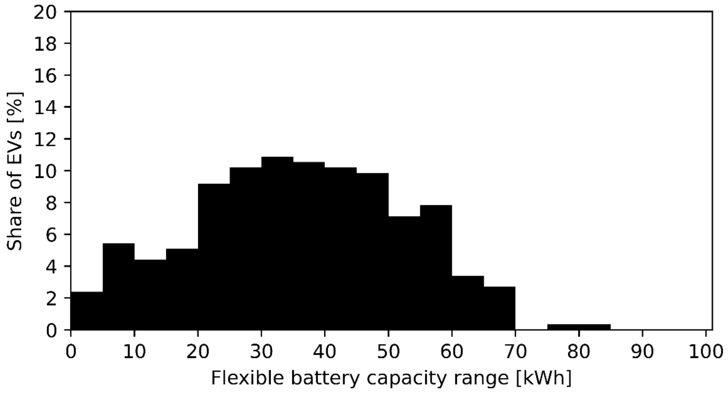

Figure 5. Flexible battery capacity range per EV.

3.2 Energy demand for EVs

Paper II investigates how the energy demand for driving and the charged energy depend on the seasons, locations and attributes of EVs. **Paper II** shows that the average daily charged energy is similar across all months, although the average daily driving distance is longer in summertime. This is because the energy consumption per km is higher in wintertime. The average charged energy depends on whether the EV is used for commuting and on the battery capacity, according to **Paper II**. **Paper II** shows that the average weekly energy use is 52 kWh for all EVs. The average weekly energy use depending on commuter category and battery capacity is shown in **Table 1**. Furthermore, **Paper I** shows that the median daily driving distance in a driving day is similar regardless of battery capacity, while the maximum daily driving distance in a driving day is longer for large-battery EVs (54–100 kWh) than for small-battery EVs (16–50 kWh).

Table 1. Average weekly energy usage levels of electric vehicles depending on commuter category and battery capacity.

	Commuters	Non-commuters
16–50 kWh battery EVs	52 kWh	33 kWh
54–100 kWh battery EVs	69 kWh	47 kWh

Figure 6 shows how much the SOC is reduced by driving in a week (**Figure 6a**), the minimum number of charging events required in a week based on the flexible battery capacity range (**Figure 6b**) and the number of days per week that each EV is charged (**Figure 6c**), categorized according to commuter category and battery capacity. The reduced SOC is calculated as the used energy divided by the battery capacity (multiplied by 100). Thus, a reduced SOC of 100% in a week indicates that the EV requires at least one charging event during the week even if the battery capacity was fully charged at the beginning of the week. The minimum number of charging events required in a week is calculated as the used energy divided by the flexible battery capacity range, as obtained in Section 3.1. For all EVs, SOC is reduced by 92% on average of all weeks. The average minimum number of charging events required in a week is 2.2, and the average number of charging days per week is 2.5.

As shown in **Figure 6**, commuters with small-battery EVs need charging (**Figure 6a** and **Figure 6b**) and actually charge (**Figure 6c**) most frequently, followed by commuters with large-battery EVs and non-commuters with small-battery EVs. Non-commuters with large-battery EVs require charging least often. The difference can be explained by the fact that commuters and non-commuters drive on approximately 83% and 68% of the days, respectively, as presented in **Paper II**. Since commuters drive on more days than non-commuters, the average daily driving distance is also longer.

The share of weeks requiring fewer than one charging event (**Figure 6b**) is approximately 25% lower than the share of weeks in which energy use is less than the battery capacity (**Figure 6a**) for all of the attributes. Furthermore, the share of weeks with one or zero charging days (**Figure 6c**) is approximately 17 and 15 percentage points lower than the share of weeks requiring fewer than one charging event (**Figure 6b**) for commuters and non-commuters, respectively, regardless of battery capacity. For example, on average for all EVs, fewer than one charging event is needed in 53% of the weeks (**Figure 6b**), although EVs are charged on one or zero days in only 36% of weeks (**Figure 6c**). This indicates that EV owners charge more frequently than is necessary, likely due to range anxiety. Charging is needed every day in fewer than 10% of weeks for all attributes, as shown in **Figure 6b**. Even commuters with small-battery EVs, the attribute with need for the most-frequent charging events, require more than three charging events per week in only 27% of the weeks.

Since EVs do not require charging on half of the days per week for more than 73% of the weeks, it can be concluded that there is substantial potential to postpone charging or to execute V2G, in response to, for example, grid congestion or spot prices. Furthermore, large-battery EVs help to avoid frequent charging, which increases flexibility to shift the charging time to alternative parking events. Note that charging needs differ between typical days and days that involve long-distance trips.

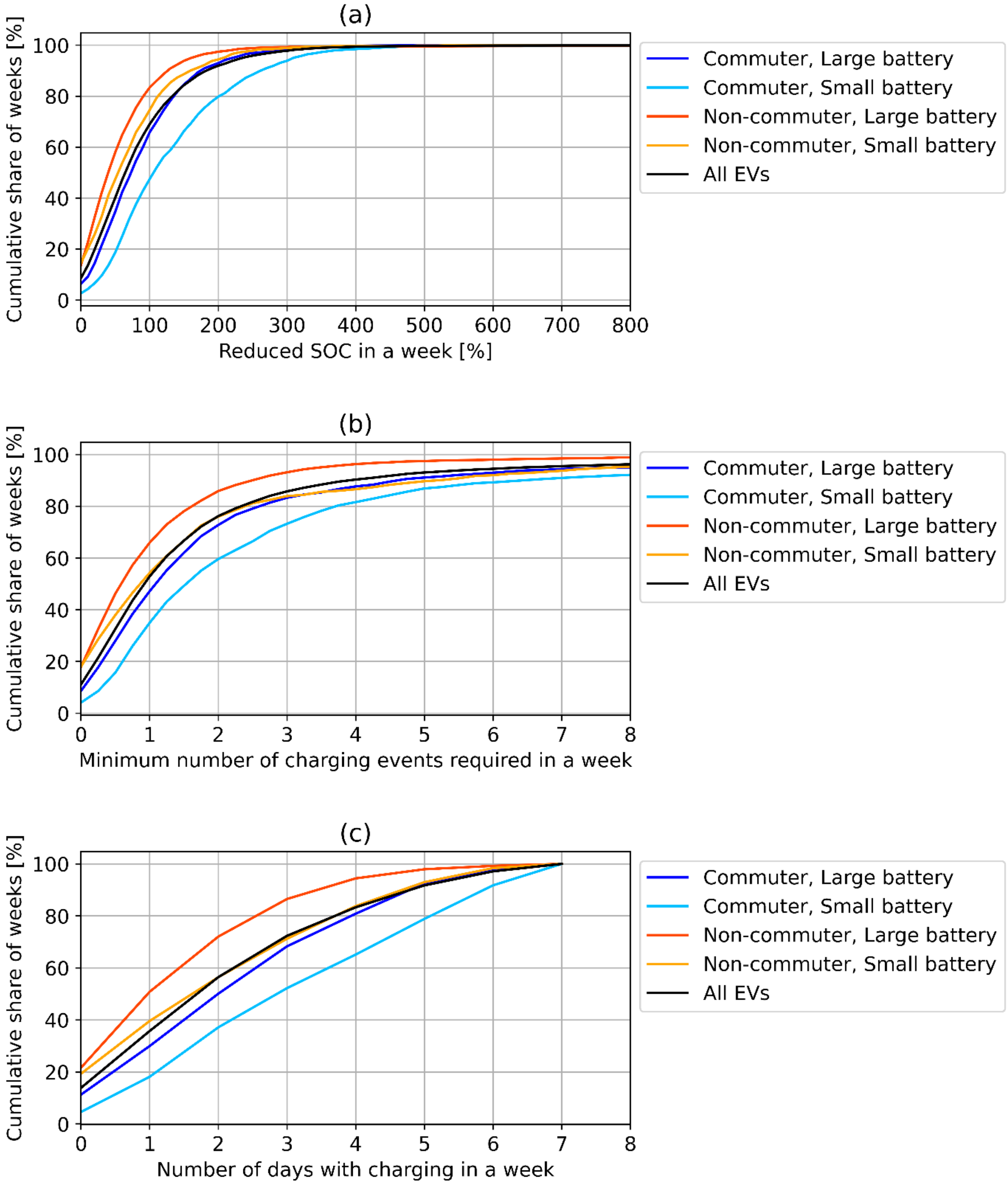

Figure 6. (a) Reduction in SOC in a week. (b) Minimum number of charging events required in a week based on the flexible battery capacity range. (c) Number of days when the EVs are charged in a week for the attributes of a combination of being a commuter or not and having a large-battery EV (54–100 kWh) or small-battery EV (16–50 kWh).

3.3 Availability of EVs for smart charging

As described in Section 2.2, the availabilities of EVs for smart charging in Case 1 and Case 2 are compared. For Case 1, the parameter that represents the availability of EVs for smart charging is the probability that a parking event occurs. For Case 2, the corresponding parameter is the probability that a parking event with charging occurs at each location category. Note that the availability of some EVs may be limited by the driving distances of the next trips.

The availability of EVs for smart charging in the two cases is shown in **Figure 7**. Shown are the probabilities for the two cases at each location category on weekdays (**Figure 7a**) and weekends (**Figure 7b**). For Case 1, the samples consist of EVs that have parked at least once at each location category. For Case 2, the samples consist of EVs that have charged at least once at each location. **Figure 7c** shows the shares of these samples relative to all EVs.

About 33% of commuters park at a workplace on weekdays (Case 1), while 10% of the commuters who have charged at workplaces make a parking event with charging (Case 2) (**Figure 7a**). Since 17% of all EVs (35% of commuters) have charged at workplaces (**Figure 7c**), the share of EVs available for smart charging at workplaces is 1.7% of all EVs (3.5% of commuters) on weekdays.

The responses to the survey indicate that 48% of commuters have access to workplace chargers. **Paper II** shows that 26% of the commuters would like to have chargers at their workplaces. The main reasons given by commuters that they do not use workplace charging are that the battery does not need charging (55%) and that charging at the workplace is expensive (45%).

If all commuters have access to chargers at their workplace, i.e., if the Case 2 sample share in **Figure 7c** matches that of Case 1, the share of available EVs of commuters would increase to 30% during daytime. Alternatively, if all commuters who have charged at workplaces are connected to a charger whenever parked (i.e., the availability of these EVs is 35% of commuters), 12% of commuter EVs would be available for smart charging. Note that commuters may be unable to plug-in due to charger occupancy or lack of chargers in specific workplace parking areas. Thus, increasing charger installation is expected to increase availability more than promoting plug-in behavior alone. However, installation is costlier than incentives to promote plug-in, and promoting plug-in could still increase availability from 3.5% to 12% of commuters.

As **Paper II** shows, the probability of parking at home (Case 1) is, on average, higher than 49% for all hours of the day (**Figure 7a**). If plug-in behavior is promoted at home, availability could increase by a factor of 2.4 on average for all hours, as seen in **Figure 7a** and **Figure 7b**. Incentives to promote plug-in at home are, therefore, important to improve availability. However, EVs owned by residents of apartments or households with multiple EVs may need to share chargers. The survey responses reveal that 12% of participating EVs share chargers with other households or have no private charger at home. Furthermore, 9% of EV owners have several EVs. In such cases, promoting plugging in behavior may prevent another EV from charging. Multi-plug chargers could, therefore, improve effectively the availability of EVs for smart charging.

Similarly, charger availability at vacation houses could increase by a factor of 2.0 on average if plug-in behaviors were to be promoted, as seen in **Figure 7a** and **Figure 7b**. Instead, availability could increase by 34% if all EVs visiting a vacation house have access there to a charger. However, most EVs visit vacation houses only a few days per year. Furthermore, availability varies little by hour because vacation houses are typically destinations, where owners stay nearby. Therefore, installing high-cost chargers may not be justified. Instead, low-cost, low-power chargers may be sufficient given the longer parking durations.

At “Other” locations, the availabilities of EVs in Case 1 and Case 2 are about 25% and 2%, respectively, during daytime, as shown in **Figure 7a** and **Figure 7b**. Therefore, availability for smart charging depends strongly on the assumptions used. Since “Other” locations include diverse locations, it is not possible to estimate the availability increase from these results alone. However, the gap between Case 1 and Case 2 is largest in this category, indicating that the assumptions made regarding availability at such locations must be carefully considered when modeling future energy systems.

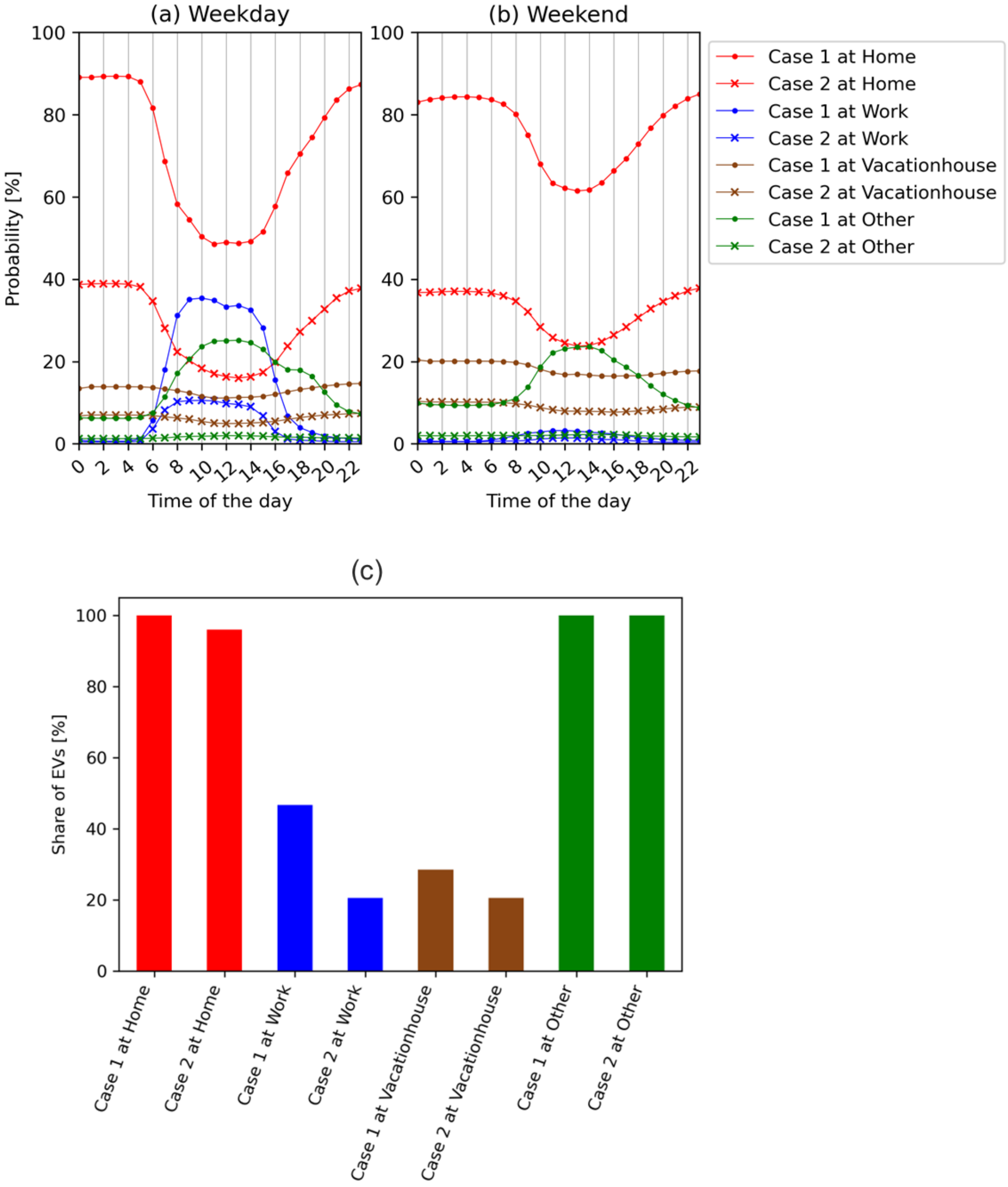

Figure 7. Availability of EVs for smart charging for Case 1 (probability that a parking event occurs) and Case 2 (probability that a parking event with charging occurs) at each location category on (a) weekdays and (b) weekends. For Case 1, the samples are EVs that are parked at least once at each location category. For Case 2, the samples are EVs that are charged at least once at each location category. (c) Share of the samples out of all the EVs.

Paper I shows that the charging probability during an overnight parking event at home depends on the SOC when arriving at home and the daily driving distance for the next driving day. **Figure 8** extends this analysis to additional charger categories and to all parking events. The samples include parking events that are longer than the shortest parking event with charging of the EV at each location, to capture occasions when EV owners have sufficient time to choose whether or not to charge.

As shown in **Figure 8**, charging probability generally depends on the SOC when arriving at the home location and the driving distance until the next arrival at home across all charger categories. This dependence is most pronounced for home-based private chargers (**Figure 8a**). The charging probability is fitted using a piecewise linear function of the SOC when arriving home and the driving distance until the next arrival at home, with a minimum probability of 0% and a maximum probability of 100%, as expressed by Equation (1):

$$p = 92.9 - 1.0\, s + 0.3d \tag{1}$$

where p denotes the charging probability, s is the SOC when arriving home, and d is the driving distance until the next arrival at home. The model exhibits a strong goodness of fit, with an R-square value of 0.94, whereas the corresponding R-square value for the other charger categories range from 0.64 to 0.78. Therefore, it is concluded that the function is well-fitted for private home chargers. For AC chargers located at vacation houses, the charging probability depends less on the driving distance until the next arrival at home than the parking events home (**Figure 8c**).

At private AC chargers located at work and "Other" locations, as well as public AC chargers, the charging probability is low when the SOC is 60% or higher, regardless of the SOC and driving distance, except when the driving distance from the workplace to home exceeds 120 km, as depicted in **Figure 8b**. When the SOC is below 60%, the charging probability increases with lower SOC and longer driving distance, indicating that EVs are charged when the remaining SOC is perceived as insufficient to return home (even if technically sufficient, depending on the owner's SOC preferences).

For public DC chargers, the charging probability is high compared with the other charger categories, as seen in **Figure 8g**. Even when the SOC remains around 40% and the driving distance to home is around 40 km, the EVs are charged on nearly 100% of the occasions. As shown in **Figure 8f**, private DC chargers show a pattern similar to that of public DC chargers, albeit with lower charging probabilities. Furthermore, when the SOC is 80% or higher, the EVs are rarely charged at private DC chargers.

These results suggest that the availability of EVs for smart charging can be increased by plugging in when charging is not urgent, i.e., when the SOC is high and the driving distance until arriving home the next time is long across all charger categories. In particular, private AC chargers at workplaces and "Other" locations are used infrequently when the SOC is high. Incentives to promote plug-in behaviors, alongside increased installation of chargers at these locations, are therefore expected to improve the availability for smart charging.

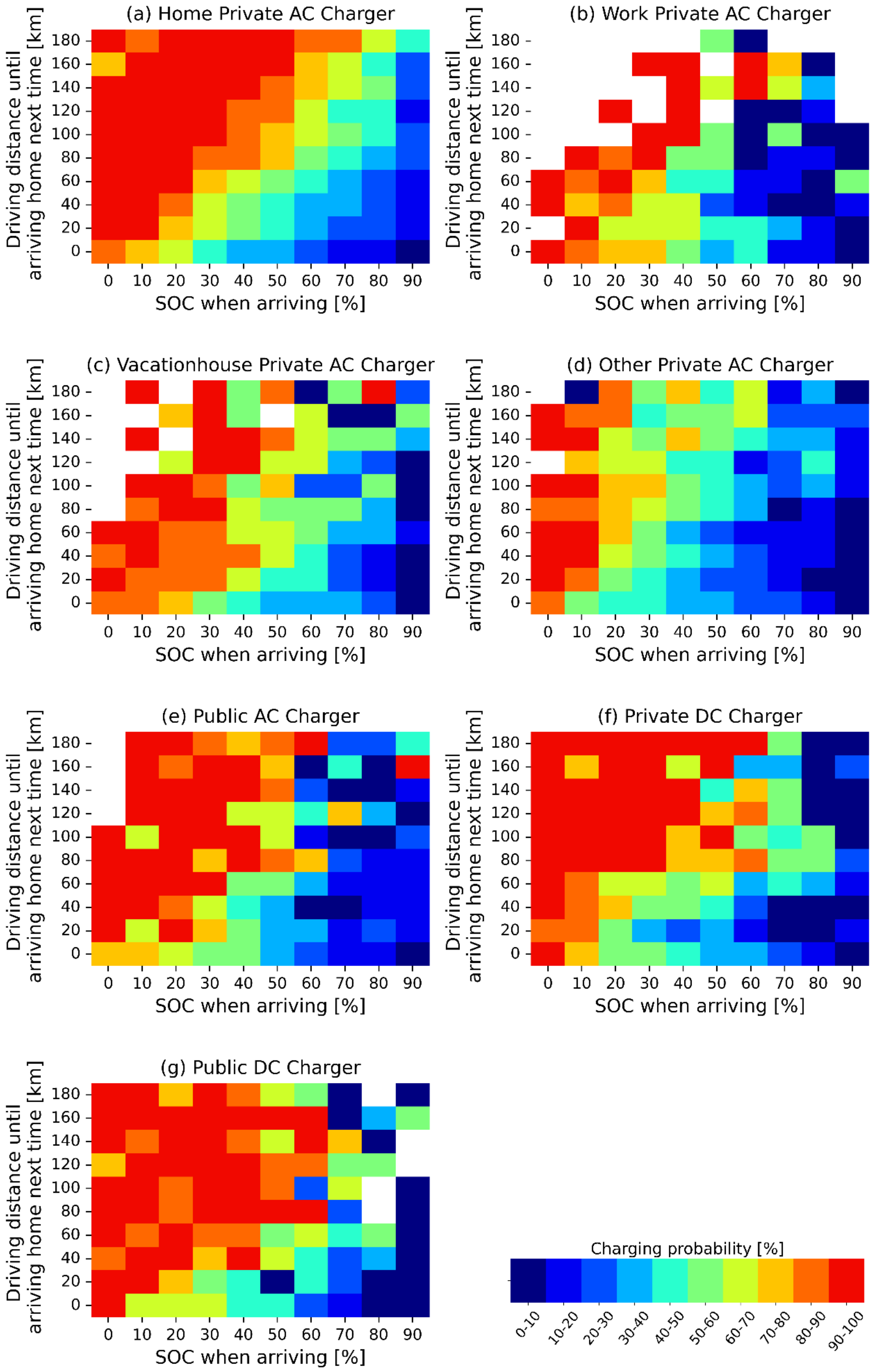

Figure 8. Charging probability based on the state of charge (SOC) when arriving at the home location and the driving distance until arriving home (or vacation home) on the next occasion for each location category. The samples are parking events that are longer than the shortest parking event with charging of the EV at each location.

3.4 Charging power need

In the case in which the EVs are assumed to be available for smart charging when plugged in according to the current charging and parking patterns, the charged energy and parking duration indicate the flexibility for smart charging during each parking event. **Paper I** shows that EVs commonly return home around 17:00 and leave home around 07:00. **Paper I** also shows that the most frequently observed parking duration at home is about four times longer than the most frequently observed charging duration at home. **Paper II** shows that the average energy charged during one parking event is 15–20 kWh, regardless of the location category.

To evaluate the flexibility for smart charging at each parking event, the minimum charging rate is defined as the charged energy divided by the parking duration. The minimum charging rate represents the lowest power needed during the parking time to supply the required amount of energy. For example, if an EV can charge at a maximum of 3.0 kW due to technical limitations and the minimum charging rate is 1.0 kWh/h, the charging power is one-third of the maximum power during the entire parking event, or the EV owner can charge for one-third of the parking duration. Thus, EVs with a minimum charging rate that is lower than the technical maximum charging power can choose with greater flexibility the charging power and/or time. **Paper III** shows the charging rates at home for several clustered EV groups.

Figure 9 shows the charged energy level and parking duration for each parking event with charging and location category. The black dashed line in the figure indicates the median of the minimum charging rare for all parking occasions with charging. As seen in **Figure 9a**, the median of the minimum charging rate needed to fulfill the charging demand is 1.1 kWh/h at home-located private chargers. The median of the minimum charging rate at vacation houses is similar to that at home, as shown in **Figure 9c**. Thus, parking events with charging at home and at vacation houses have strong flexibility to shift the charging time, assuming that each EV owner has access to their own charger and is not sharing it with other cars in the same household or other households.

The median of the minimum charging rate is 2.1 kWh/h for workplace private AC chargers (**Figure 9b**). The level of flexibility is lower at workplaces than at private residences, although substantial flexibility is still expected. However, only 48% of commuters have access to chargers at their workplace, so even if the degree of flexibility is high, it is currently limited by the charging infrastructure. Notably, although the survey shows that only 8% of commuters have no access to a charger at home, 35% of the energy charged at workplace AC chargers is charged by these commuters. Thus, extensive development of the charging infrastructure is important for those who have limited access to chargers at home.

Other private AC chargers and public AC chargers show similar medians of the minimum charging rates (3.0 kWh/h and3.2 kWh/h, respectively), as shown in **Figure 9d** and **Figure 9e**. For DC chargers, public DC chargers show extremely high minimum charging rates (median:33.3 kWh/h), as shown in **Figure 9g**, due to short parking durations and high maximum charging power. Private DC chargers, in contrast, show a median of the minimum charging rate of 6.5 kWh/h (**Figure 9f**).

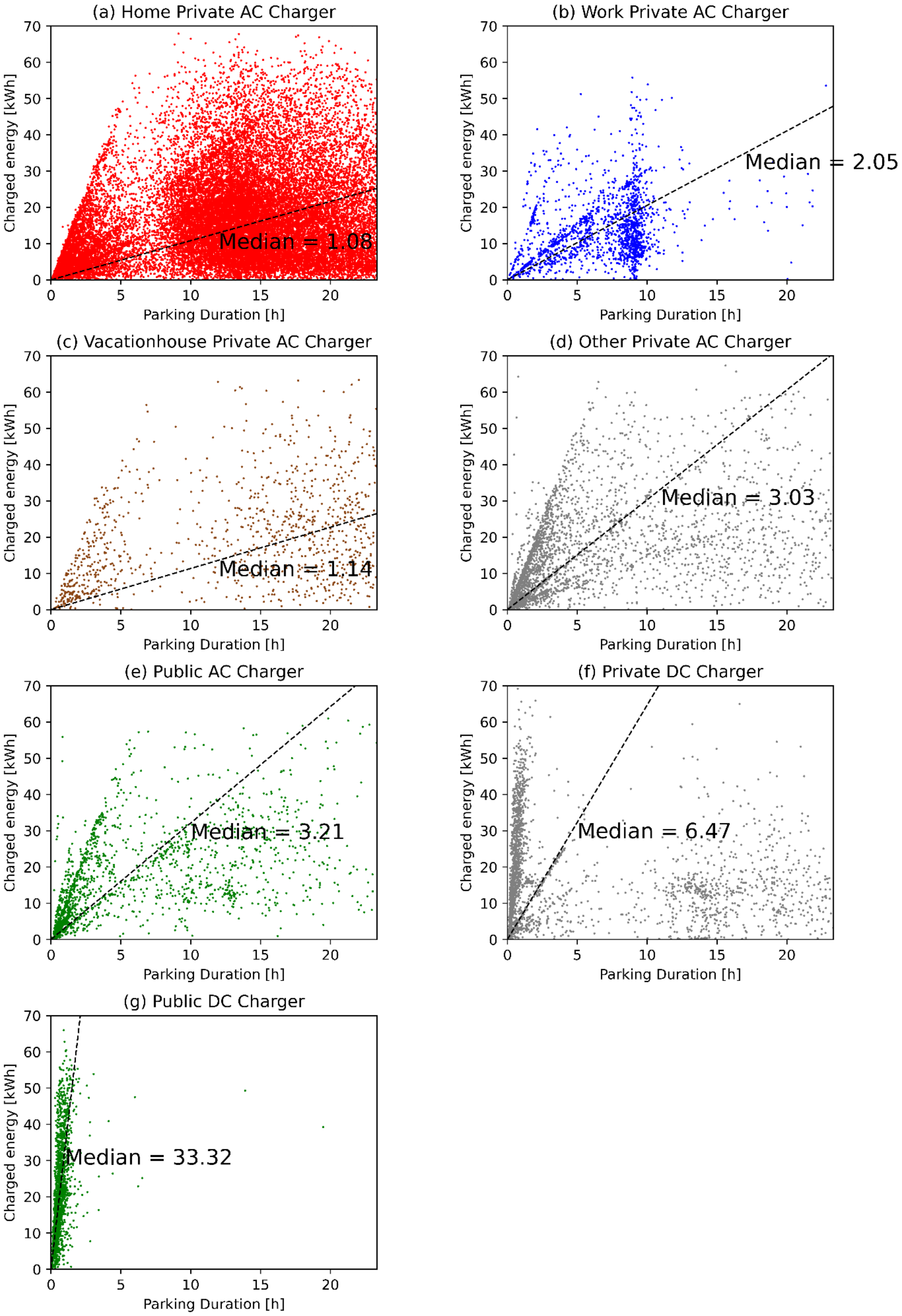

Figure 9. Charged energy level and parking duration for each parking event with charging at (a) home, (b) workplaces, (c) vacation house, and (d) other places; The dashed black line indicates the median of minimum charging rates.

Figure 10 shows the maximum charging power of chargers at each location category, in descending order for each category for AC chargers (**Figure 10a**) and DC chargers (**Figure 10b**). Note that the charging power refers to the input power to the EV batteries, rather than the output power from the chargers. As shown in **Figure 10a**, the most-common maximum charging power of private home chargers is 10 kW, with 28% of private home chargers having charged at this level. A charging power of 3 kW is also common (22% of private home chargers), and 84% of private home chargers can charge at 3 kW or higher. The most-common maximum charging power of private chargers at vacation houses is 2 kW, with a share of 34% (**Figure 10a**). Thus, with the current set of chargers, the flexibility of charging is higher at home than at vacation houses, although substantial flexibility still exists at vacation houses.

The most-common maximum charging power of private AC chargers at workplaces is 2 kW (25% of workplace private AC chargers), although chargers with 3 kW and 10 kW outputs represent 23% and 13% of the share, respectively, as shown in **Figure 10a**. Considering the current large share of low-power chargers, the level of flexibility is lower at workplaces than at private residences. However, there is also a substantial share of relatively high-power chargers, in that 44% of workplace AC chargers can charge at 5 kW or higher, as seen in **Figure 10a**.

The most-common maximum charging power of public AC chargers is 10 kW, and 47% of public AC chargers can charge at 9 kW or higher. The most-common maximum charging power of private AC chargers at "Other" locations is 3 kW, with a share of 18%. Due to their similar minimum charging rates and the current trend observed for the charging power of AC chargers, charging events at public AC chargers have greater flexibility than Other private AC chargers. The maximum charging power levels of DC chargers are similar between public and private DC chargers, as seen in **Figure 10b**. Thus, for DC chargers, only long charging events at private DC chargers are expected to provide flexibility for smart charging.

From these results, it is concluded that charging events at private home chargers exhibit the greatest flexibility. In addition, as mentioned in Section 4.3, promoting more-frequent plugging in increases the availability of EVs for smart charging. At workplaces, the flexibility is more limited compared to at home and at vacation houses, but EVs are parked at workplaces mainly during the daytime. Therefore, parking events at workplaces play important roles, in that they enable charging of photovoltaic (PV)-generated energy and contribute to balancing services, such as ancillary services.

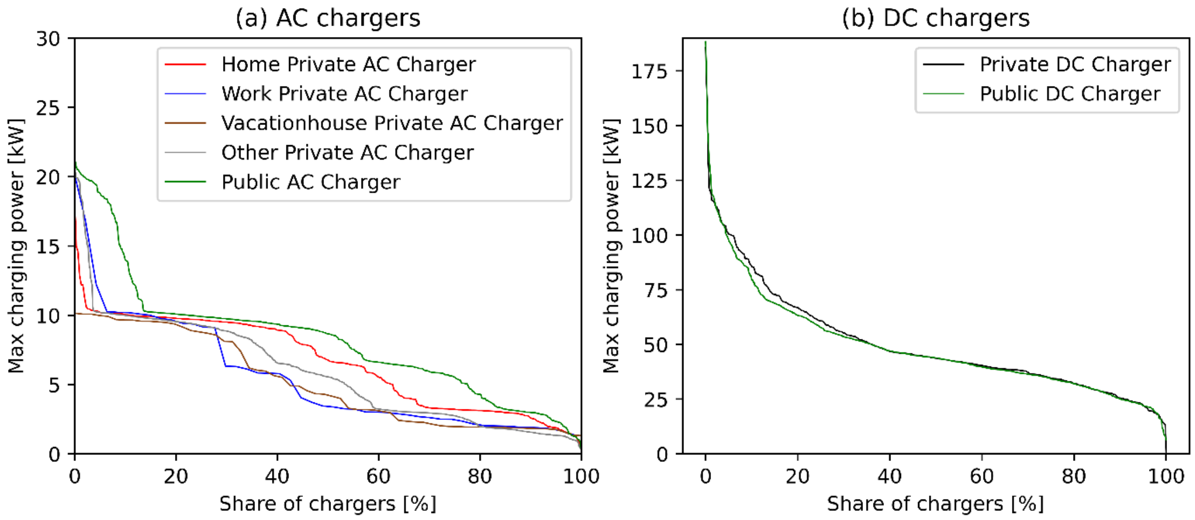

Figure 10. Maximum charging power of chargers at each location in descending order for each charger category for: (a) AC chargers; and (b) DC chargers.

3.5 Utilization of flexibility for smart charging by current EV owners

The flexibility of charging at home is utilized by some EV owners in different ways, such as charging in response to dynamic electricity prices or rooftop PV electricity generation. **Paper I** shows that only 40% of overnight charging events are initiated immediately after arriving home for the EV owners who live in a detached house, whereas the corresponding percentage for those who live in an apartment is 77%. According to the survey responses received, 50% of those who live in a detached house report that they charge when the electricity price is low. Overall, 32% of the participating EV owners have rooftop PV, and 13% report that they charge their EVs when the PV system generates electricity. In addition, 51% report that they charge as soon as they arrive home if the SOC is low. Of the EV owners who live in a detached house, 51% have hourly electricity contracts, 37% of whom start charging automatically without manually setting the charging start time.

Figure 11a shows the charging probability at each hour depending on the difference in spot price from the 24-hour moving average for EV owners with hourly and non-hourly household electricity contracts. For those with hourly electricity contracts, the charging probability is shown separately depending on the SOC at the beginning of the hour. The charging probability at each hour is calculated as the number of hours for which an EV is charged at home divided by the number of hours for which the EV is parked at home.

EV owners with hourly electricity contracts charge their EVs depending on the spot price when the spot price is lower than the 24-hour moving average, while the charging probability is almost constant regardless of the spot price for those with non-hourly contracts, as seen in **Figure 11a**. When the spot price is higher than the 24-hour moving average, the charging probability is about 12%, regardless of the type of household electricity contract.

The charging probability is higher for those with hourly contracts than for those with non-hourly contracts because the average daily charged energy is higher (hourly contract:7.5 kWh; non-hourly contract:5.3 kWh). In other words, those EV owners with hourly contracts use more energy for driving. There are several reasons for this. One reason is that EV owners with hourly contracts tend to live in a detached house, and commuters also tend to live in a detached house. Since commuters drive longer distances than non-commuters, the average daily charged energy is higher for those who live in a detached house than for those who live in an apartment. Another reason is that more of the detached houses are located in the countryside than in cities. Overall, 24% of those who live in a detached house live in the countryside, as compared with only 3% of those who live in an apartment. In addition, EV owners who are living in the countryside use 30% more energy than those living in large cities. It is also likely that EV owners who use large amounts of energy choose hourly electricity contracts to reduce their charging expenses.

For EV owners with hourly electricity contracts, the lower the SOC, the higher the charging probability when the spot price is lower than the 24-hour moving average, as demonstrated in **Figure 11a**. However, when the spot price is 20 €/MWh higher than the 24-hour moving average or even more expensive, the charging probability is about 12% regardless of the SOC. When the spot price is 0–20 €/MWh higher than the 24-hour moving average, the charging probability is higher when the SOC is in the range of 0%–40% than when the SOC is >40%

As a result, the patterns of charged energy during the daytime differ between the electricity contract types. **Figure 11b** shows the average charged energy at each hour for weekdays and weekends for each contract type. Thus, EV owners with hourly electricity contracts charge most of their energy at home during night-time on weekdays. During weekends, the night-time peak is lower, and a small peak appears around 14:00–15:00 during weekends because more EVs are parked home during daytime on weekends than on weekdays. Electric vehicle owners with non-hourly contracts charge more during the evening, i.e., around 14:00–21:00, than those with hourly contracts. **Paper I** also shows that controlled charging at detached houses results in a pronounced peak in charging with start time at exactly 22:00, 23:00, and 00:00 h.

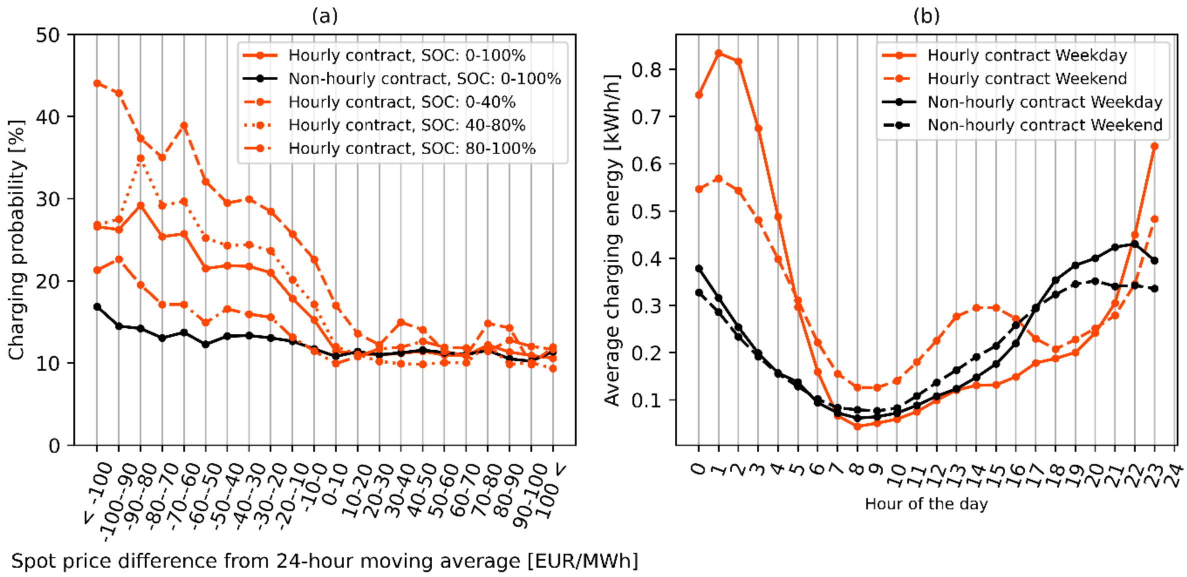

Figure 11. (a) Charging probability at each hour depending on the difference in the spot price from the 24-hour moving average for the EV owners who have hourly contracts and non-hourly contracts for household electricity. For those with an hourly electricity contract, the charging probability is plotted separately depending on the state of charge (SOC) at the beginning of the hour. (b) Average charging energy level at each hour for weekdays and weekends for each electricity contract.

3.6 Clustering

In **Paper III**, the 262 EVs with logged data that cover more than 8 months without critical missing data are assigned to three clusters (termed the '3C case') and five clusters (termed the '5C case'), to examine the generalizability of EV characteristics for smart charging. The number of clusters (three clusters and five clusters) are chosen because these cases show relatively high silhouette scores and contain a sufficient number of EVs in the smallest cluster (threshold: 20 EVs), as concluded in **Paper III**. However, if the threshold for the minimum acceptable cluster size is lowered from 20 EVs to 10 EVs, the case with eleven clusters shows a higher silhouette score than the 5C case, as seen in **Figure 3**. Therefore, this thesis extends the clustering analysis to also include 11 clusters (termed the '11C case'). It should be noted, however, that clusters with very low numbers of EVs may represent collections of outliers, making the results less-robust. It should also be noted that using 11 clusters may render the computational load for energy systems models burdensome. Nevertheless, by comparing the 5C and 11C cases, it is possible to identify the simplifications that are introduced when reducing the number of clusters from 11 to 5.

Figure 12 shows the average probability that a parking event occurs at home in each hour of the day on weekdays and weekends for the 3C, 5C and 11C cases. The characteristics of each cluster are summarized in **Table 2**.

When comparing the 3C and 5C cases, several clusters exhibit similar characteristics, as can be seen in **Table 2**. Cluster 3-1 and Cluster 5-1 represent non-commuters. Commuters generally tend to stay away from home more often, drive longer distances, and have smaller-battery EVs than non-commuters. Therefore, these non-commuter clusters are expected to have a high level of flexibility with a large battery, high probability of parking home on weekdays, and low charging demand. Cluster 3-2 and Cluster 5-3 represent commuters with EVs that have small batteries. These clusters are expected to have relatively low flexibility due to their low probability of parking at home on weekdays and their need for substantial amounts of energy. Cluster 3-3 and Cluster 5-5 represent commuters with EVs that have large batteries. Their lower probability of being at home on both weekdays and weekends, combined with a higher charging demand than Cluster 3-2 or Cluster 5-3, limits their flexibility. However, their large batteries allow charging to be shifted to other parking events.

In addition to these clusters that are common to both the 3C and 5C cases, the 5C case includes a cluster of EVs that maintain a high SOC (Cluster 5-2) and a cluster with a low probability of parking at home at night (Cluster 5-4). Thus, the number of clusters must be chosen by considering the trade-off between computational load and the level of detail applied to representing the EV characteristics.

When the number of clusters is extended from five to eleven, some clusters exhibit combinations of characteristics that are not present in the 5C case, including clusters with extreme values. For example, Cluster 5-4 (low probability of parking at home at night) shows about 80% during night-time on weekdays (**Figure 12c**), while Cluster 11-10 shows 65% at the same hour (**Figure 12e**). The cluster of EVs that maintain a high SOC (Cluster 5-2) is split into two clusters depending on the battery capacity (Cluster 11-2 and Cluster 11-3). Cluster 11-4 is dominated by non-commuters with small-battery EVs. Cluster 11-5 also consists largely of non-commuters, albeit with high energy demands (i.e., higher than some commuter-dominated clusters). Cluster 11-8 represents commuters with small-battery EVs but with energy demands that are similar to those of non-commuters. Cluster 11-9 is expected to have a low level of flexibility, since these EVs are commuters with small-battery EVs and high energy demands, necessitating frequent charging even when the SOC is relatively high. Cluster 11-11 represents commuters with the highest energy demands (20% higher than the EVs in Cluster 5-5) and the lowest probability of parking at home (except for Cluster 11-10 on weekends), as seen in **Figure 12**. Note that Cluster 11-4, Cluster 11-9 and Cluster 11-11 contain less than 20 EVs, which may indicate outliers and reduces the robustness of the analysis.

In conclusion, the 11C case captures several characteristics that are not visible when using only five clusters (the 5C case), such as: clusters that maintain a high SOC separated by battery size; a cluster of non-commuters with small-battery EVs; commuters with low energy demands; commuters with small-battery EVs and high energy demands; and commuters with extremely high energy demands.

However, using 11 clusters in energy systems models would significantly increase the computational load compared to using five or three clusters. If more clusters are included, other simplifications may be required, such as shortening the simulated time period or reducing the temporal or geographic resolution. Other options are to remove clusters that contain a low number of EVs or to merge them with other clusters. In the 11C case, this would result in eight clusters, which would still represent individual EVs better than the 5C case. When reducing the number of clusters from five to three the computational load is an important consideration. However, it is also important to note that the clusters in the 5C case that capture characteristics that are not present in the 3C case represent non-negligible shares of the EVs (Cluster 5-2: 17%; Cluster 5-4: 24%).

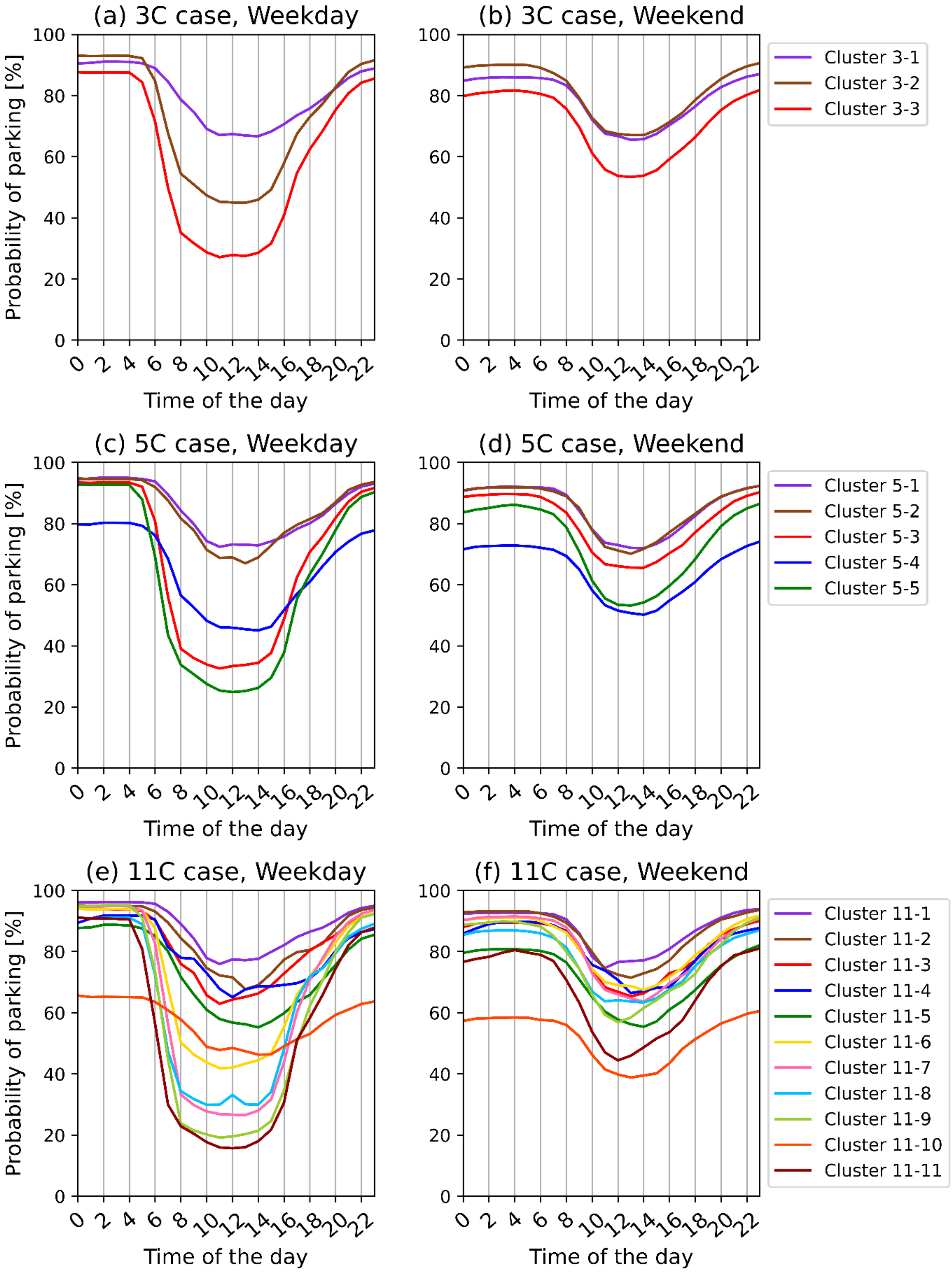

Figure 12. Average probability that a parking event occurs at home in each hour of the day in weekdays and weekends for: (a: weekday, b: weekend) the 3C case; (c: weekday, d: weekend) the 5C case; (e: weekday, f: weekend) the 11C case. Source: based on Paper III.

Table 2. Summary of the clusters. The cells are shaded with the deepest red for the largest value and the deepest blue for the smallest value in each column. The color indicator of each column is independent from each other column. Source: based on Paper III.

Cluster	Share of commuters [%]	Average battery capacity [kWh]	Average daily charged energy [kWh]	Probability that a parking event occurs at home during daytime (at noon) [%]		Aggregated SOC [%]		Average lower SOC threshold for charging decisions [%]
				weekday	weekend	min	max	
Cluster 3-1	14	67	7	67	67	39	91	26
Cluster 3-2	65	39	6	45	67	43	95	35
Cluster 3-3	76	64	12	28	54	41	89	30
Cluster 5-1	12	64	6	73	73	37	87	23
Cluster 5-2	14	56	6	69	71	52	98	45
Cluster 5-3	89	38	8	33	66	39	96	31
Cluster 5-4	34	68	8	46	52	36	88	24
Cluster 5-5	81	68	15	25	53	33	88	32
Cluster 11-1	9	67	5	77	77	40	86	25
Cluster 11-2	16	43	5	72	72	53	98	50
Cluster 11-3	15	73	7	64	67	56	98	45
Cluster 11-4	25	40	6	65	71	31	86	26
Cluster 11-5	25	70	10	57	58	35	85	18
Cluster 11-6	80	38	6	42	69	43	98	30
Cluster 11-7	88	68	9	27	66	40	90	28
Cluster 11-8	81	38	7	33	64	37	93	24
Cluster 11-9	100	42	12	20	57	37	98	40
Cluster 11-10	9	66	7	48	40	45	92	28
Cluster 11-11	100	72	19	16	44	27	92	37

CHAPTER 4

Main conclusions

The present study analyzes the characteristics of EVs and EV owners related to flexibility for smart charging, based on real-world logging data collected from 394 privately owned EVs and the survey responses received from the EV owners. The results show substantial potential for flexibility with regard to smart charging from several perspectives, while also highlighting the limitations that must be carefully considered when estimating flexibility or implementing it in energy systems models.

Using the lower SOC threshold for charging decisions and the SOC when charging ends, the flexible battery capacity is calculated to be 59% on average. However, when EVs are regarded as a single aggregated battery, the aggregated SOC remains within the range of 60%–80% throughout the entire logging period. Thus, it is important to consider the individual flexible battery capacity range of each EV, which varies from 0 kWh to70 kWh.

The charged energy is relatively constant across different months because the average driving distance is higher in summer, while energy consumption per kilometer is higher in winter. The charged energy, however, varies with commuter category and battery capacity. Despite these differences, charging is needed on fewer than half of the days per week for 73% of the weeks, regardless of commuter category or battery capacity. Furthermore, EVs are charged more frequently than the minimum number of charging events required per week. This indicates the potential for postponing charging for smart charging purposes, particularly for non-commuters with large-battery EVs.

Regarding the availability of EVs for smart charging, the availability is estimated to differ by more than a factor of two between the two cases: the case where EVs are assumed to be plugged in whenever they are parked; and the case where EVs are assumed to be plugged in only when they charge during the parking event. Therefore, careful consideration is needed when estimating the availability of EVs for smart charging. Installing chargers at workplaces is important for increasing the number of EVs available for smart charging, although few EVs need to charge at work to fulfill their commuting distances.

For parking events with charging, the minimum required charging rates indicate the highest flexibility at home, although the AC chargers at the other location categories also show substantial levels of flexibility. This flexibility at home is utilized by EV owners with hourly electricity contracts, who select charging times when the spot price is lower than the daily average price.

Furthermore, the logged EVs are clustered into three, five and eleven clusters, resulting in clusters with distinct characteristics. When the number of clusters increases from three to five, a cluster with low probability of parking at home during night-time and a cluster that maintains a high SOC appear. When the number of clusters is extended to eleven, some clusters exhibit combinations of characteristics that are not present in the case with five clusters, including clusters with extreme values. Clusters with characteristics that differ from the typical commuter or non-commuter patterns are obtained.

CHAPTER 5

Further research

The present study and the three papers included in this thesis analyze EV usage patterns, including cluster analyses. The present study shows that the highest potential flexibility is for smart charging during parking events at home, and that EV owners with hourly electricity contracts utilize this flexibility to reduce their charging costs. In terms of future work, it would be of interest to investigate in greater depth the different charging behaviors at the home location. Understanding real user behaviors, such as how EV owners choose to charge at home under the influence of different factors, is essential. In addition to charging strategies in response to the spot price, rooftop PV and stationary batteries in households are likely to influence charging behaviors. The survey responses show that 32% of the participating EV owners have rooftop PV, and 21% own stationary batteries. Since charging strategies are expected to comprise a mix of several behaviors, future work could examine the circumstances under which each strategy is implemented. The results can then be compared with the responses to the survey in which EV owners describe their charging strategies. This analysis could also be extended to include seasonal variations and differences across user attributes.

The present study also shows that the availability of EVs for smart charging at “Other” locations in the future will depend strongly on assumptions, since about 25% of EVs are parked during the daytime on weekdays, while charging occurs during only approximately 8% of the parking events. Therefore, it is of interest to investigate in greater depth the use of chargers at “Other” locations, including public charging stations. Such analyses would clarify under which circumstances public charging stations are used and would provide an assessment of the impact of fast charging on battery degradation. User experiences of public charging stations are also of interest for future work, including queueing, charging cost and EV owners’ preferences for using public chargers, which are addressed in the survey responses.

In this work, EVs are analyzed by dividing them into two battery-capacity groups: small-battery EVs (16–50 kWh); and large-battery EVs (54–100 kWh). These analyses clearly indicate the differences in driving and charging patterns depending on battery size. It is also of interest to identify the battery capacity threshold that best separates the driving and charging patterns. This can contribute to understanding EV usage patterns and specifying EVs that meet users’ needs. Furthermore, although the analyses use nominal battery capacity in the present study, the battery capacity that is actually usable for driving may be more limited due to battery degradation. Therefore, it is relevant to analyze battery degradation and EV usage patterns while accounting for this effect. **Paper II** shows the EV usage patterns depending on the EV attributes. It is also of interest to identify the factors that drive EV user behaviors using methods such as factor analysis, multiple regression and logistic regression. These methods may better connect the survey responses with the EV logging data and identify important factors for each EV usage pattern.

For the cluster analysis in **Paper III**, it will be of interest to compare the results with clustering based on other input parameters. For example, if the temporal parking patterns at home are in focus, the temporal parking patterns could be clustered using time-series clustering methods. These approaches may also contribute to predicting EV user behaviors. Furthermore, it will be of interest to compare the results of clustering with clustering based on the survey data using Latent Class Analysis (LCA). The cluster analysis in **Paper III** produced clusters that represent specific attributes, such as being a commuter, whereas LCA can provide clusters from different perspectives. In **Paper III**, each key parameter related to flexibility for smart charging is quantified and analyzed for each cluster. However, the level of flexibility when considering all the parameters is quantified when implementing the clusters in electricity grid simulations. Therefore, the clusters for each case that depend on the number of clusters and input parameters should be compared at different scales, such as the national levels and regional levels.

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