Assessment of real-world driving patterns for electric vehicles: an on-board measurements study from Sweden

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Assessment of real-world driving patterns for electric vehicles: an on-board measurements study from Sweden

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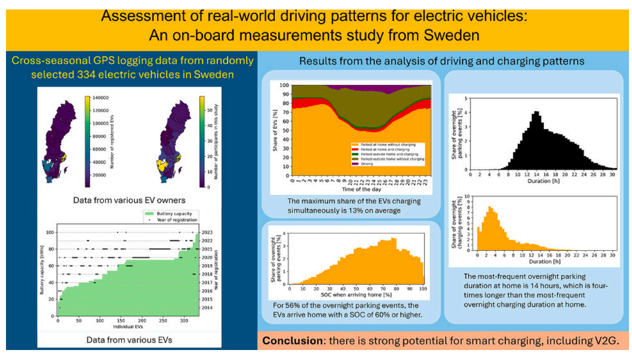
HIGHLIGHTS

- Driving and charging patterns of electric vehicles (EVs) are analyzed.
- The analysis is based on cross-seasonal GPS logging data from 334 EVs in Sweden.
- The most-frequent overnight parking duration is four-times longer than charging.
- The EV owners who are living in a detached house shift charging time more often.
- The EVs arrive home with a high SOC regardless of battery capacity.

GRAPHICAL ABSTRACT



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ABSTRACT

This study presents an analysis of the driving and charging patterns of passenger, battery-powered electric vehicles (EVs) in Sweden. The analysis is based on 1 year of GPS logging data acquired through the on-board diagnostics port for 334 randomly selected EVs in Sweden. Included are 55 EV models with battery capacities in the range of 16–100 kWh. The results show that 70 % of the electricity is charged at the home location, of which 86 % is charged during overnight parking events. The maximum share of the investigated EV fleet charging simultaneously is 13 % on average (at 00:10 h). For 56 % of the overnight parking events, the EVs arrive home with a state of charge (SOC) of 60 % or more. For the EVs that arrive at the home location with 60 % SOC, they are charged during 64 % and 34 % of the overnight charging events at home for the small (16–50 kWh)-battery and large (54–100 kWh)-battery EVs, respectively. The most-frequent parking duration is 14 h, which is about four-times longer than the time needed for charging and, thus, offers possibilities for flexible charging in time and vehicle-to-grid services. In summary, this study shows that there is a large potential for smart/flexible charging at home, since the EVs often arrive home with a relatively high SOC and are parked at home, between two trips, for a much longer time than is needed to recharge the battery.

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1. Introduction

In order 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, the number of battery-powered EVs reached 1.5 million in 2023 [3]. The number of registered EVs in Sweden, which is the country in focus in this study, has increased dramatically during the last few years, from 9122 in 2016 to 291,678 in 2023 [4], corresponding to 5.9 % of the passenger car fleet [4].

The electricity system in Europe, and that in Sweden, will most likely contain a larger share of wind and solar power in the future [5]. Since wind and solar power generation levels vary depending on the wind velocity and solar radiation, respectively, 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 might be used to shift load in time, i.e., moving charging to low-demand hours. EVs might also be adapted to discharge energy back to grid, so-called vehicle-to-grid (V2G) services. Studies are needed to estimate: (i) the impact of EVs on the electric grid; (ii) the need for charging infrastructure; and (iii) the potential, and possible benefits, of smart charging and V2G, such studies require knowledge of the driving and charging patterns of EVs. One also needs to understand the attitudes and motivation of EV owners with respect to the use flexible charging. To date, only a limited number of studies have been conducted on the charging and driving patterns of passenger EVs. This likely reflects the fact that it is only recently that there has been a dramatic increase in the number of EVs, with the main growth seen over the last few years. Thus, until recently, there were limited numbers of EVs in each region, and most of the passenger EVs were owned by high-income individuals living in the larger cities, so not necessarily representative of the typical EV passenger fleet of a country.

Previous studies on the charging and/or driving patterns of privately owned EVs have typically suffered from one or several of the following limitations:

a) They are based on EV driving patterns using data collected from travelling surveys or diaries [] [] [] [][6–9];
b) The logged data are from fossil-fueled vehicles or plug-in hybrid vehicles with small batteries [7,10–14];
c) They include a low number of EVs [14–17];
d) They cover only a few EV models [8,18] [19–21];
e) They are limited to charging data that are collected at chargers (driving behavior cannot be acquired) [] [] [][22–24];
f) The vehicles included are not privately owned [25–27];
g) They consist of only EVs with a low battery capacity, i.e., relatively old models [28–30]; and
h) They are based on the data collected over a short period [6,7,15,25].

Calearo et al. [31] reviewed articles on vehicle charging and driving patterns published during the last two decades until 2021. Among the articles reviewed, there were 14 articles that based their results on driving and charging data collected from surveys, 15 articles with data collected from internal combustion engine vehicles (ICVs) and/or EVs, and 21 articles with data from private and public chargers. However, Calearo et al. [31] concluded that all the datasets of driving and charging patterns were either based on ICVs or a low number of EVs.

Patil et al. [32] reviewed 44 articles published between 2017 and 2021 that used driving and/or charging data from surveys and the logging of vehicles (20 articles from surveys, 18 from logging EV/ICVs, 6 with data from chargers), to investigate actual or possible charging behaviors from the perspective of the charging infrastructure. Andrenacci et al. [33] also reviewed studies that investigated the charging behaviors and charging decisions of EV owners. The articles reviewed in the paper of Andrenacci et al. [33] consist of 46 survey-based studies and 18 studies based on data logged from individual EVs or chargers. All of the studies reviewed by Patil et al. [32] and Andrenacci et al. [33] can be categorized as one of the assumptions listed above (a–h).

Alemanno et al. [6] used a survey conducted among EV owners to analyze how EVs can meet the driving needs of car drivers in six European countries (France, Germany, Italy, Poland, Spain, and the UK). The data were collected from 3723 EV owners by asking them to write a trip diary for 7 consecutive days. The participants in the study of Alemanno et al. [6] were chosen based on city size, gender, age, level of education, and occupational status. Alemanno et al. [6] concluded that the average daily driving distance differs between the countries, with 70–90 km for Spain and Poland, 50–60 km for Italy, France and Germany, and around 40 km for the UK. They proposed that the average daily driving distance was within the battery range for most EV models, and that it was similar for weekdays and weekends. Furthermore, they concluded that the average duration of parking during night-time was 16 h or longer in all six countries. However, the data only covered 1 week of a year, and since they were not measured but based on a log written by the participants, there may have been mistakes and missed trips.

Zhang et al. [17] analyzed the driving and charging patterns of 41 privately owned EVs (10 different vehicle models) in Beijing, China, using data collected via the on-board diagnostics (OBD) port over a period of 6–25 months depending on the car. The aim of the study was to predict more accurately the future charging demands, so as to design an efficient charging infrastructure. They concluded that the EV owners typically started the first trip of the day during the time interval of 06:00–09:00 and completed the last trip of the day between 17:00 and 22:00. They also showed that the state of charge (SOC) when starting to charge was between 40 % and 60 % for 34 % of the EVs, and that the average charging duration was 173 min. However, 41 vehicles is a rather limited sample, and the study included 10 mainstream EV models and the participants were recruited online or on the spot as volunteers, which are limitations in terms of obtaining reliable results for a whole fleet.

Taljegard et al. [10] analyzed the benefits of smart charging and V2G for the electricity systems in Sweden, Norway, Denmark and Germany using a cost-optimization model. The driving patterns in the model were based on GPS-logging data from 429 ICVs in Västra Götaland County in Sweden collected in the data-logging campaign conducted by Björnsson [13] and Karlsson et al. [12]. Karlsson et al. [12] concluded that 7 % of the cars were being driven at 17:00 (the hour when most cars are driven) and 5 % were being driven at 08:00. Using these data, Taljegard et al. [10] concluded that installing EVs contributes to a gain in terms of wind power generation and a smoothing of the net load, reducing the need for investments in peak-power plants. However, since the GPS logging was based on ICVs, the assumption made in that study was that EVs have the same driving patterns as ICVs. Thus, there is no information about charging patterns.

Suzuki et al. [21] developed a simulator that generates synthetic charging profiles assuming different charging strategies, using driving and charging patterns data derived from the telematics of 14,000 Nissan LEAF 24 kWh EVs in the US (January 1, 2015 to December 31, 2016). The aim was to clarify the impact of EVs on the future charging demand. They conclude that EV owners make the decision to charge EVs depending on the SOC when they arrive home or at their workplace. However, the results obtained from charging pattern analyses can vary if the battery capacity is changed.

Xu et al. [28] and Sun et al. [29] analyzed charging modes and locations based on the data from 500 EVs (250 private EVs and 250 commercial EVs) over a period of 2 years. Each EV was logged for about a year all around Japan. Although the models of the logged EVs were not disclosed, Sun et al. [29] stated that the logged EVs had only two battery sizes, corresponding to driving ranges of 120 km and 180 km. Since the logging for the study carried out by Sun et al. [29] was conducted from 2011 to 2013, the EV models were limited and contained only small batteries.

Dodson et al. [22] analyzed the data for 8.3 million charging events

Table 1
Parameters included in the trip dataset in this study.

Parameter	Description	Unit
Time of start/end of a trip event	Start time and end time of a trip event	YY:MM:DD HH:MM:SS
Coordinates of the end of a trip event	Longitude and latitude when the trip ended	(x,y)
Driving distance	Distance between the start and end of a trip	km

collected from public/private/workplace chargers across the UK in the period of 2017–2018, with the aim of improving a model of the EV charging demand. The study concluded that the peak charging demand, as observed between 19:00 and 20:00 during weekdays, was dominated by charging at home. However, in order to analyze the potential for smart charging, one needs to follow the charging and driving patterns of individual vehicles and not only separate charging events.

To the best of our knowledge, there are no published studies that have analyzed charging and driving data collected from hundreds of randomly selected EVs for a cross-seasonal period using on-board GPS equipment and taking into account the various models and battery sizes that represent the entire EV market in a country. Thus, there is a need to collect and study real driving and charging patterns, including SOC, for a high number of EVs of various models, located in both urban and rural settings, over a longer time period (such as an entire year).

The aim of this study is to analyze the characteristics of the charging and driving patterns among EV owners, so as to define the potential for smart charging and V2G at the home location. This study uses data on driving and charging patterns, as well as the battery status for 334 randomly selected EVs distributed across Sweden. The collection of data is performed using on-board GPS equipment plugged into the OBD port. The dataset enables us to draw conclusions about the driving and charging patterns of current EVs, using Sweden as an example. In this paper, the collected data are used to analyze the driving distances of EVs, the parking time at the home location, and the parking/charging behaviors at the home location during night-time.

2. Method

This chapter is divided into the following subsections: logging equipment and parameters logged (2.1); the process of selecting the EV owners (2.2); the methods used for handling missing data and problems with the logging equipment (2.3); description of the parameters analyzed in this study (2.4); and the method used to estimate the home location (2.5).

2.1. Logging equipment and parameters

Equipment from Geotab Inc. (Oakville, ON, Canada) was used for logging the driving and charging patterns in this study. The logging was performed using the OBD port in the EVs. The Geotab-device draws power from the auxiliary battery with 2.5 mA. It should therefore not have an impact on the performance of the EV battery. The logged data were transmitted to a database provided by Geotab [34]. The Geotab database consists mainly of trip data (see Table 1) and status data for vehicles and batteries (see Table 2). A trip event is defined as the time period during which the EV is not parked. Parking is defined as the period during which the "ignition" is turned off and/or the driving speed is kept at 0 km/h for more than 200 s. Trip data are a dataset of parameters recorded for each trip event. The parameters include the start time and end time of a trip, the coordinates of the EV at the end of a trip, and distance traveled (see Table 1). Other parameters in the trip dataset not used in this study include the maximum and average speed and idling duration.

Table 2 presents the parameters in the status dataset, including information on the two logging methods (1 and 2) used for storing the values recorded for the parameters. The start and end of charging are recorded when the EV shows the signal for start or end of AC or DC charging as part of the status dataset, as well as the SOC, odometer values, energy to battery during charging, energy demand for driving and charging power, as shown in Table 2. Other parameters in the status dataset not used in this study include the battery and outside temperatures and energy charged to an on-board charger. In order to limit the amount of stored data, the status data are recorded only when there is a change in the parameters using one of the following two methods (see also Geotab [34]):

Method 1. Parameters are recorded with a certain difference compared to the previous value. The parameters using Method 1 to decide which data to store are the SOC and odometer values. For a more-detailed description of Method 1, see Fig. A1 in Appendix A. Odometer values are typically stored for every 1–10 km and SOC is stored for every 0.5–2.0 % change in value (depending on the car model).

Method 2. For the parameters in the status dataset other than the start and end of charging, SOC, and odometer values, only some measured data-points are stored using the Ramer-Douglas-Peucker algorithm [35]. The reason for using this algorithm is to reduce the volume of logged data to be stored, without losing important information. The algorithm works as follows. Draw a line from a logging data-point A to B. If the

Table 2
Parameters included in the status dataset in this study.

Parameter	Description	Unit	Logging method
Start/end of a charging event	The type of charging (AC or DC) is distinguished.	0: End 1: Start AC charging 2: Start DC charging	–
SOC	State of charge of the battery capacity.	%	1
Odometer values	Reading of the odometer	km	1
Energy to battery during charging	The energy going into the battery via charging accumulated from the first logged data.	kWh	2
Energy demand for driving	The energy discharged from the battery from all non-charging sources accumulated from the first logged data.	kWh	2
Charging power	Charging power measured at the battery. The electricity voltage is 230 V in Sweden (e.g., single-phase, 16 A is assumed to be 3.68 kW). Note that the charging power measured in this study is the charging power to the battery of the EV, which represents the charging power after losses incurred in the on-board charger and during other processes in the vehicle. The efficiency of the charging power depends on the car model and the charging current and varies between 65 % and 95 % [36].	kW	2

most-distant point recorded between A and B (let us say point A′) is more distant than a threshold from the line AB, point A′ is stored. Then draw a line from A′ to B and repeat the same process until the distance from the line to the most-distant point becomes less than the distance of the threshold value. See Fig. A2 in Appendix A for an example of Method 2, as well as Geotab [34].

2.2. Participants in the study

The participants of this study were private EV owners resident in Sweden who were randomly selected by Statistics Sweden (SCB) among owners of EVs. The selection by SCB was conducted using data from the Swedish Vehicle Register (*Fordonsregistret*) (December 31, 2021), the Register of the Total Population (*Registret över totalbefolkningen*), the Database of Household Residences (*Hushållens boende*) from 2021, and the Geographical Database (*Geografidatabasen*) from December 31, 2020 to December 31, 2021. The data collected from the above databases were limited to:

- Passenger EVs.
- Vehicles in traffic.
- Privately owned vehicles.
- Pure EVs (i.e., no hybrids or plug-in hybrids).
- EV models for which the Geotab-device could be connected to the OBD port and transfer charging and driving data.

The result was a total of 33,260 EV in the sampling frame to invite for the logging according to the five selection criteria listed above. In total, 55 models (definitions based on the EV Database [37]) were included in the selection of EVs to be invited for the study. A random selection was made within six strata after excluding unspecified urban area type, unspecified housing type, and special housing and other houses. From this, the following residential categories and house types were included:

- Residential categories:
  - o Non-urban area, i.e., with fewer than 200 inhabitants
  - o Small town, i.e., town with fewer than 25,000 inhabitants
  - o Large urban area, i.e., urban area with 25,000 or more inhabitants
  - o *Unspecified (not included in this study).*
- Housing types:
  - o Detached houses
  - o Apartment buildings
  - o *Special housing (not included in this study)*
  - o *Other houses (not included in this study)*
  - o *Unspecified (not included in this study).*

From the six selected strata (33,260 EV owners), 4436 EV owners were selected as a stratified unbound random sample. Among the 4436 candidates who were invited, 480 accepted the invitation. Yet, the number of logged vehicles analyzed in this paper is limited to 334. The reason for not including all the EVs where the owners accepted the invitation is that some were excluded due to issues with the logging equipment in the car and in some cases the EV owners had sold the car. Table 3 gives an overview of the participants and how they are distributed according to housing type, and how these housing types are

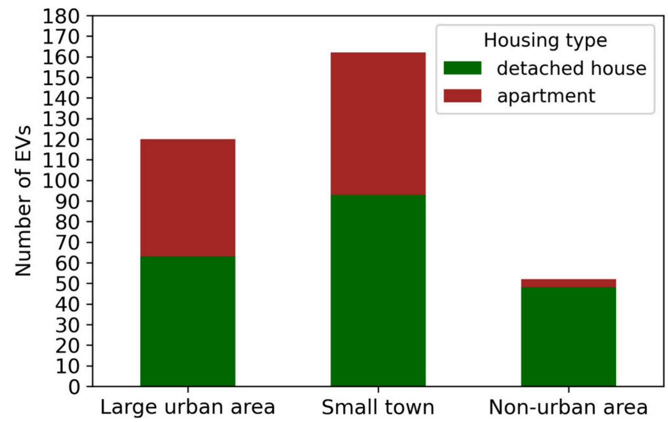

Fig. 1. Number of participants included in this study for each housing type and each residential category.

distributed between non-urban areas, small towns and large urban areas (i.e., the six strata), as illustrated in Fig. 1. The participants are in a broad range of age from 23 to 87 years old (57 years old on average). In this study, 84 % of the participants are more than 40 years old, corresponding number for all privately owned passenger cars in Sweden is 80 % [38]. The age and gender distribution of the participants in this study is shown in Figs. D1 and D2 in Appendix D.

Fig. 2 shows the number of registered EVs in 2023 [4] (2a) participating in this study (2b) per county in Sweden. Fig. 3 shows the battery capacity and registration year for all the EVs included in this study. The *x-axis* of Fig. 3 shows the individual EVs numbered in ascending order according to battery capacity (light-green bar). The *y-axis* to the left indicates the battery capacity of each EV. Each dot in Fig. 3 represents the year of registration for each EV, with the year on the right-hand *y-axis*. The battery capacity was retrieved based on information on the car model name, model year, year registered in Sweden, and vehicle weight. The battery capacity is the nominal capacity collected from the EV Database [37]. As shown in Fig. 3, the battery capacity tends to increase with year of registration, although there is a broad span of battery capacities (there are only four cars included that were registered in Year 2023, as seen in Fig. 3). According to Fig. 3, all of the EVs registered in 2016 or before have a 25-kWh or smaller battery, while all of the EVs which have a 50-kWh or larger battery were registered in 2018 or later.

The first logged data are from October 11th, 2022 and the last logged data used in this study are from September 18th, 2024. The number of logged EVs each day is shown in Fig. 4a. The first phase of the logging (i.e., until December 2022) was a test phase designed to make sure that the equipment was working properly. In the second phase, equal numbers of participants were included from each of the population/housing types. In Phase 2 of this study (i.e., January 2023 to December 2023), the majority of the data used in this study were logged, as shown in Fig. 4a. Phase 3 started in December 2023, in which additional EV owners invited to the study were divided equally between the strata (see Appendix B for more information on the different phases). Fig. 4b shows the number of logging days per EV. In this study, 192 EVs were logged for longer than 365 days and 305 EVs were logged for longer than 180 days. Due to technical issues with the installation of the equipment, nine

Table 3
Numbers of participants and candidates summed for all three phases.

	Total	Detached houses			Apartment buildings		
		Non-urban area	Small town	Large urban area	Non-urban area	Small town	Large urban area
EVs in the sampling frame (meeting the eligibility criteria)	33,260	5337	12,869	9538	27	899	4590
Invited EVs (randomly selected from the sampling frame)	4449	336	1540	911	27	737	898
EV owners accepting the invitation	480	66	148	86	7	89	84
Participants included in this study	334	48	93	63	4	69	57

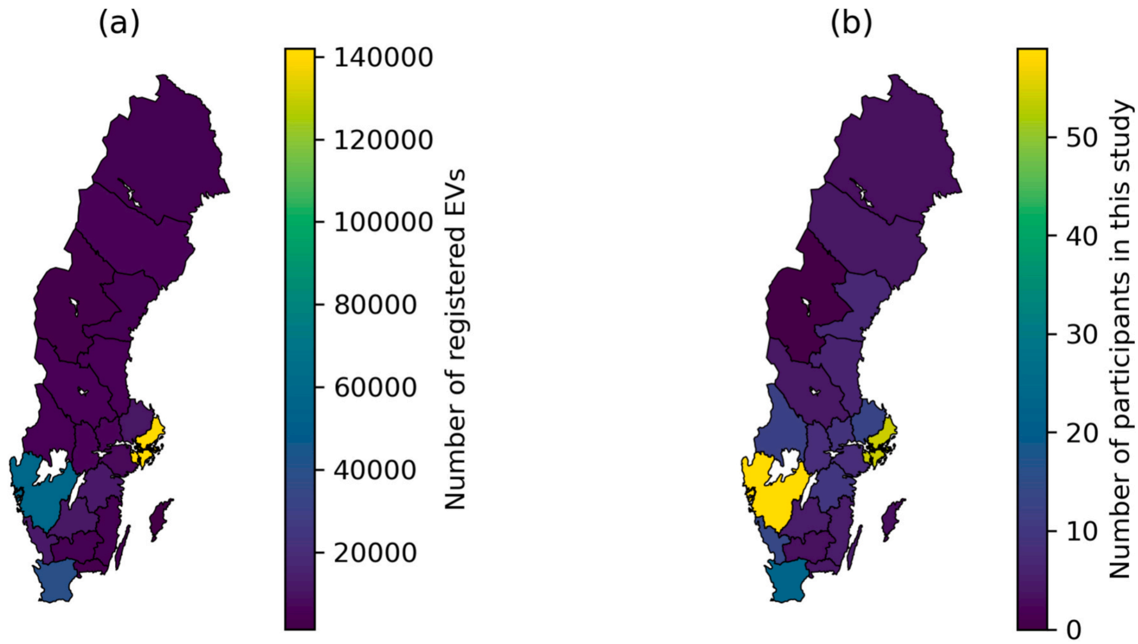

Fig. 2. (a) Number of registered EVs and (b) the number of participants included in this study in each county in Sweden.

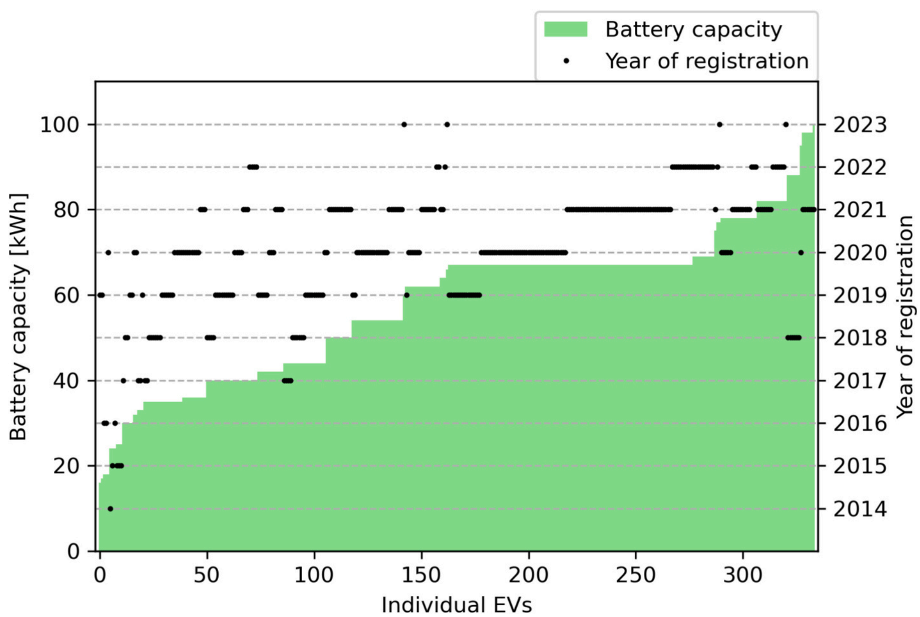

Fig. 3. Battery capacities (light-green bars with left *y-axis*) and the years of registration (dots with right *y-axis*) for the 334 EVs included in this study. Each dot for the years of registration represents each EV. The individual EVs are in ascending order according to battery capacity. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

EV models were excluded from the study in the pilot/s phase after the invitation and before the logging started. In the third phase, these technical issues were resolved and these models were included in the study.

2.3. Handling missing data and problems with logging equipment

There are three possible categories of missing data: (1) periods for which all data are missing: (2) periods for which trip data are missing while status data are recorded; and (3) periods for which each parameter of the status data is missing during charging or trip events. Each of these types of missing data are described below and the ways in which they are handled are also described. In this study, we have also calculated the rates of missing data for all parameters for all EVs. Equations defining periods for which data are missing and the rate of missing data are listed in Appendix C. Table 4 shows the degree of missing data of each parameter calculated in Sections 2.3.1–2.3.3.

2.3.1. Periods for which all data are missing

The main reasons for data not being measured and/or stored are: (1) problems linked to communication between the OBD unit and car; (2) long-term loss of connection between the OBD unit and database; (3) software problems in the OBD unit; and (4) the OBD unit being unplugged by the EV owner for a period of time. Fig. 5a shows (red part) the EVs for which the data logging is complete ("All/Part of the data complete") and those for which all the data are missing (black part).

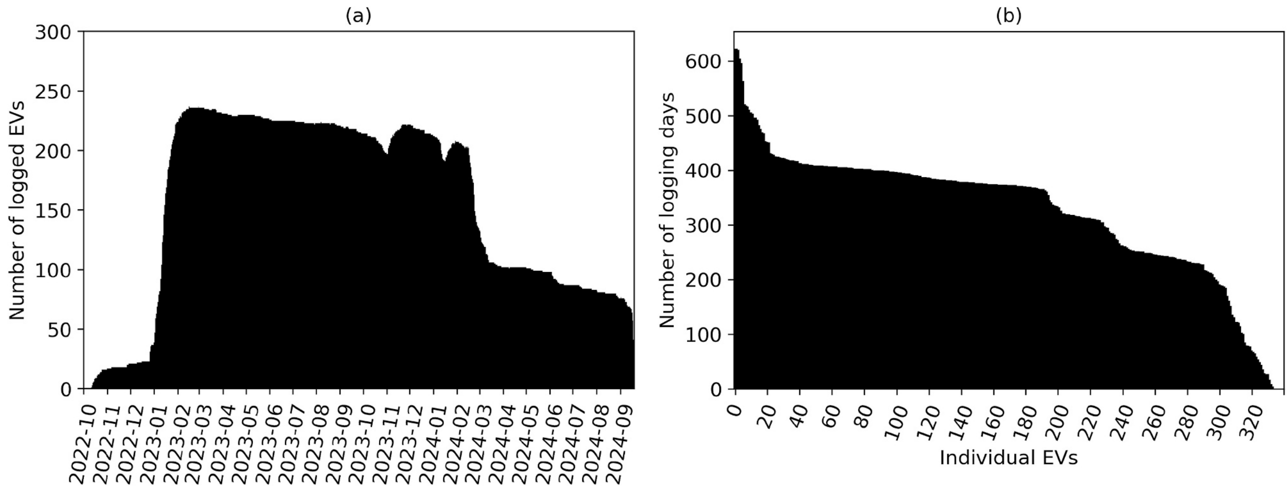

Fig. 4. (a) Number of logged EVs on different days during the logging period in this study and (b) number of logging days for each EV. The individual EVs are in descending order according to the number of logging days.

Table 4
Missing shares of data for the different parameters investigated in this work.

	All EVs	75 % percentile	95 % percentile	EV with the highest rate (per parameter)
All data	6 %	6 %	31 %	93 %
Trip event	0 %	0 %	1 %	75 %
Start/end of a charging event	10 %	8 %	62 %	100 %
Odometer values	8 %	5 %	48 %	100 %
SOC during trip event	7 %	4 %	43 %	100 %
SOC during charging event	0 %	0 %	1 %	100 %
Energy charged to battery during charging	0 %	0 %	0 %	1 %
Energy demand for driving	5 %	3 %	35 %	96 %
Charging power	2%	0 %	5 %	100 %

Fig. 5b shows the same data for the logging days for each individual EV.

Periods with missing status and trip data can be identified using the odometer values and SOC. This is possible because these parameters are recorded with a certain difference from the previous value (see logging Method 1 in Section 2.1). During a recorded trip event and/or charging event, the differences from the previous data for the odometer values and SOC are recorded as shown in Fig. 6. As can be seen in Fig. 6, most of the odometer values (99.998 %) are recorded within a 10-km increase from the previous value. In the same way, most of the SOC data (99.7 %) are recorded within a 2 % increase or decrease from the previous value.

Periods for which all data are missing are defined as follows (all the criteria listed below must be met):

- The difference between two odometer values recorded after each other exceeds a threshold value of 10 km.
- The difference between two recorded SOC values exceeds a threshold value of 2 %.
- The driving distance based on the trip data does not satisfy the difference observed for the two odometer values.
- Status data are not recorded. (Only periods longer than 1 h without recording status data are taken into account, so as to avoid defining the period between the status data during the same trip or charging event as a missing period.)
- Trip data are not recorded.

2.3.2. *Trip data are missing while status data are recorded*

Periods for which trip data are missing but status data are recorded

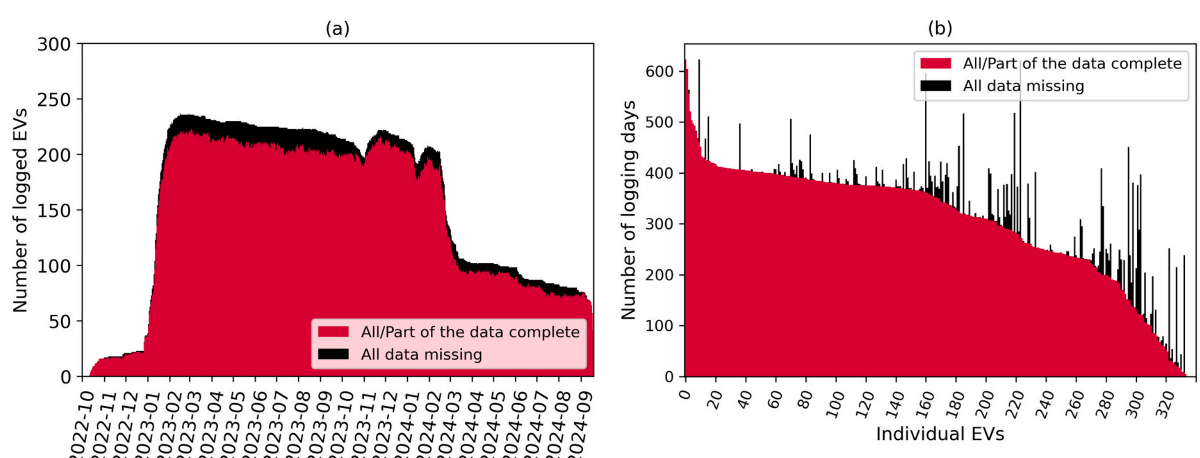

Fig. 5. (a) Number of logged EVs per day and (b) number of logging days per EV with all or part of the data complete (red) and all data missing (black). Panel (a) is in chronological order, while in panel (b) individual EVs are in descending order according to logging days with all/part of the data complete. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

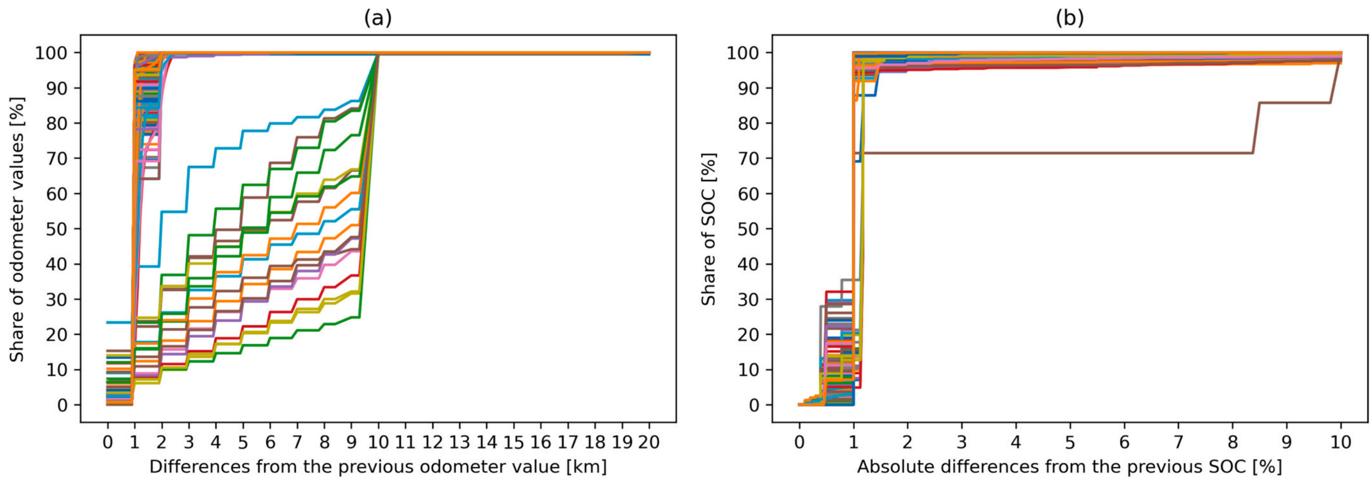

Fig. 6. Differences from the previous (a) odometer values and (b) SOC. Each line shows one EV, so there are 334 lines in total.

can be defined based on the odometer values. If the odometer values are recorded without missing data-points between two recorded trip events (i.e., recorded at an interval shorter than the 10-km threshold), the difference in odometer values between two recorded trip events is regarded as the distance of the missing trip data. The locations where the EVs are charged and from which they started to drive cannot be identified if trip data are missing before the events, since the information on the coordinates is composed of only the locations where the trip events end. The locations where charging events start and end, and where trip events start after missing trip event data are regarded as unknown places if trip data are missing.

2.3.3. Status data are missing

If the SOC is increased without any charging data recorded between two trips and/or charging events, charging data are missing. This is the case if the SOC is increased by more than the threshold value of 2 % between two trip events or charging events. Periods for which the other status data (i.e., SOC, odometer values, energy to battery during charging, energy demand for driving, charging power) are missing during trip events or charging events are defined with the periods of trip or charging events without recording the evaluated parameter.

2.3.4. Rates of missing data for trips and status

Table 4 shows the shares of missing data for all the parameters together and individually (i.e., how large share of the data that is missing). The shares of missing status data for parameters during trip and charging events (i.e., odometer values, SOC, charging energy, consumed energy during trip, charging power) are evaluated in comparison to the duration of the recorded trip or charging events. Fig. 7 shows the shares of missing data for each parameter and EV in increasing order. As shown in Table 4 and Fig. 7, the data for most of the parameters are complete (i.e., a small share of the data is missing). In total for all the EVs, 6 % of the logging duration is estimated to be periods for which all data are missing. Overall, 95 % of the EVs are missing all data for 31 % or less of the logging period. However, some vehicles are missing a major share of the data for some parameters, e.g., for 5 %

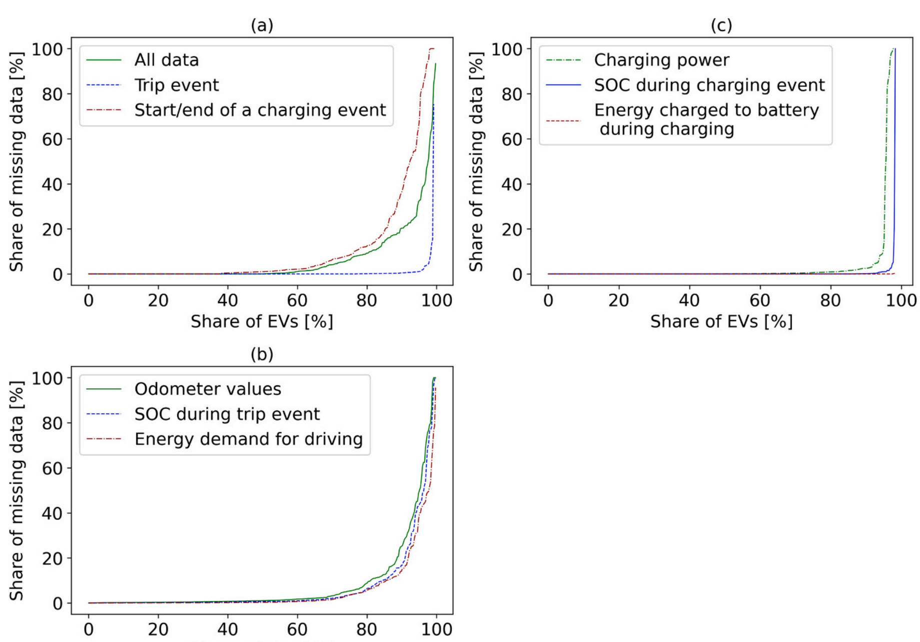

Fig. 7. Shares of missing data for: (a) all data and trip/charging events; (b) odometer values, SOC during trip event, and energy demand for driving; and (c) charging power, SOC during charging event, and energy charged to the battery during charging.

Table 5
Concepts used in this study.

	Definition of concept
Large-battery EVs Small-battery EVs	• Large-battery EVs: 54–100 kWh • Small-battery EVs: 16–50 kWh Note that there was no EV with a battery capacity lower than 16 kWh or higher than 100 kWh, and there was no vehicle with a battery capacity between 51 kWh and 53 kWh.
Yearly driving distance	The odometer values when logging has reached 365 days.
Logging days	All days when the OBD unit is plugged in, excluding periods for which all the data are missing.
Driving days	All days that the EVs are driven, i.e., days for which trip data have been recorded. Days with missing trip data or days with 0 km of driving are not counted as "driving days".
Daily driving distance	The sum of the distances of all trips that started during a day (i.e., within 24 h). If no trip occurs during a day, the daily driving distance is 0 km. Days with 0 km are not included when calculating, e.g., the median daily driving distance.
Home location	The location at which the EV is parked most often at 03:00 within 1 km of the address of the EV owner's residence (for a detailed description of the method used to find home location see Subsection 2.5).
Night-time parking event	Parking event during which EVs are parked at 00:00 (midnight) but not parked before 12:00 (noon) on the day before or after 12:00 on the same day. This means that the maximum number of hours that an EV can be parked during a night-time parking event is just under 24 h. This can be compared to overnight parking events that can be an unlimited number of days.
Daytime parking event	Parking event during which the EV is parked at 12:00 (noon) but not parked before 00:00 on the same day or after 00:00 the next day. Parking events, other than those defined as night-time parking events or daytime parking events, are not used for the analyses of night-time/daytime parking events.
Overnight parking event	The last parking event of the day (i.e., before 00:00 the next day) at the home location. This can be an unlimited number of days and can start before 12:00, compared to night-time parking that is limited to 24 h and starts always after 12:00.
Overnight charging event	Charging that takes place during an overnight parking event. The charging events during an overnight parking event are combined, i.e., overnight charging event is counted as one even if several charging events occur during an overnight parking event.
Charging probability (during an overnight parking event)	The number of overnight charging events at the home location divided by number of overnight parking events at the home location. Only the events by the EVs which experienced charging at home location are counted.
Charging probability (outside home location)	The number of days that the EV is charged at locations other than the home location divided by the number of driving days.
Location and charging/trip or not	Numbers of EVs divided into the following five • Parked at home without charging • Parked at home and charging • Parked outside home and charging • Parked outside home without charging • Driving All days in the logging period for each EV are included, except if there is a period for which all trip data are missing.
Number of driving days between two overnight charging events	Counted only in the case where no charging event is recorded and no charging event is missing between the two overnight charging events.
Maximum charging power at home location	The highest charging power measured at the home location. The analysis of maximum charging power is conducted with two groups: • Low maximum charging power: 3–4 kW • High maximum charging power: 9–10 kW The EVs with maximum charging power other than the above (i.e., other than 3–4, 9–10 kW) are excluded so as to clarify the difference in charging pattern depending on the maximum charging power.

of the EVs, 48 % or more of the odometer values are missing. About 1 % of the EVs are missing charging power data for more than 50 % of the duration of the charging events. The rate of missing for trip events for all EVs is significantly low, although a few EVs have a high missing rate (evidenced as the highest missing rate of 75 % in Table 4). Charging events are missing for 10 % of the parking events for all the EVs when SOC was increasing.

The missing data rate differs depending on car model. Table E1 in Appendix E shows the number of EVs per car model with missing data rate for different parameters higher than 20 %. Renault ZOE tend to miss a lot of data compared to other models, e.g., 35 % of the Renault ZOE in this study show a missing data rate higher than 20 % for start/end of a charging event. Another example is Volkswagen ID series, where 27 % are estimated to miss more than 99 % of the data of start/end of a charging event. Half of the BMW i3 EVs are estimated to miss more than 70 % of the data of SOC during trip.

2.4. Analyses conducted in this study

Table 5 defines important terms used in this study. Table 6 shows the number of EVs included in each analysis in this study based on a threshold for missing data. Only EVs with less than 20 % missing data for the parameters in focus are included if (1) missing data have a large influence on the results, such as charging probability during an overnight parking event depending on SOC, and (2) the analyses require a reasonable amount of data. Furthermore, in the analysis of some parameters that require a reasonable amount of data only EVs recorded for at least 180 days where included (excluding periods with all data missing) as seen in Table 6.

2.5. Estimation of home location

The locations for parking and charging are in this study categorized into home locations and other locations, to enable an analysis of the potential for smart charging/V2G at the home location. The home location for each EV is defined based on both the coordinates of the parking location and the address of the residence of the EV owners provided by SCB. All parking locations are grouped into several parking areas, since many EV owners will use different parking locations when at home (except for those having their own parking lot). The Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm [39] is used for grouping coordinates of parking events into the same parking area. DBSCAN is a clustering method that links spatial data-points that are close to each other. DBSCAN has the advantage that the number of clusters does not need to be defined beforehand. In addition, nearby points can be distinguished within the same cluster regardless of the shape of the clusters. Given these features, DBSCAN is suitable for grouping the coordinates with locations whose number is not fixed, and parking areas can take many geographic forms, such as streets. The home location of each EV is defined as the location where the EV was parked the most times during night-time (at 03:00). Parking locations farther than 1 km from the address of the EV owner's residence are

Table 6
Conducted analyses and thresholds to choose EVs and number of EVs for each analysis.

Conducted analyses	EVs included in the analysis	Number of EVs
• SOC when arriving home for overnight parking events • Daily driving distance • Overnight parking duration • SOC when ending overnight charging events • Time when starting overnight charging events • Time of arriving/leaving home for night-time/daytime parking events • Location and charging/trip or not	All EVs	334
• Elapsed time from arriving home to the beginning of overnight charging events • Overnight charging duration	All EVs where a rate of missing data for start/end of charging events is <20 %	283
• Driving days • Median and maximum daily driving distances for each EV	All EVs with a logging period of >180 days (when excluding days for which all data are missing) and where the rate of missing data for trip events is <20 %	289
• Average energy consumption for driving	All EVs with a logging period of >180 days (when excluding days for which all the data are missing), and the rate of missing data for trip events is <20 %, and the rate of missing data for energy demand for driving is <20 %	271
• Charging probability during an overnight parking event (depending on SOC)	All EVs where the rate of missing data for start/end of charging events is <20 %, and the rate of missing data for start/end of SOC during trip event is <20 %	257
• Charging probability during an overnight parking event (depending on next daily driving distance) • Charging probability outside the home • Number of driving days between two overnight charging events	All EVs with a logging period of >180 days (when excluding days for which all data are missing), and the rate of missing data for trip events is <20 %, and the rate of missing data for start/end of a charging event is <20 %	253
• Share of energy charged at home locations	All EVs with a logging period of >180 days (when excluding days for which all data are missing), and the rate of missing data for start/end of a charging event is <20 %, and the rate of missing data for energy charged to the battery during charging is <20 %	242
• Yearly driving distance	All EVs where the difference from first to last time reading of odometer value >365 days	169
• Overnight charging duration (depending on maximum charging power)	All EVs where the rate of missing data for charging power is <20 %, and the rate of missing data for start/end of a charging event <20 %, and only EVs with battery capacity >54 kWh and a charging power of 3–4 or 9–10 kW.	62

excluded.

Fig. 8 gives an example of the estimation of home location made for one EV in this study. The longitude and latitude are on the *x*-axis and *y*-axis, respectively. In Fig. 8, we have adjusted the left-bottom point to 0 degrees, so as not to reveal the exact location of the EV owner. The red cross represents the location of the home address. In this example, the parking locations are classified into six clusters as a result of the clustering made with DBSCAN.

The home location is assumed to be only one for each EV, although 9 EV owners may have moved to other locations during the logging period. In addition, vacation houses, which are common to own in Sweden, are not defined as home locations in this study, even though EVs might be parked there for long time periods and be charged with a private charger.

3. Results

3.1. Daily and yearly driving patterns

Fig. 9 shows the yearly driving distances for EVs that were driven for at least 1 year. The results show that the median yearly driving distance is 14,442 km and that 40 % of the EVs have an annual driving distance of more than 16,000 km. The average yearly driving distance for EVs is 16,530 km (95 % confidence interval: [15,360 km, 17700 km]), which is longer than the average yearly driving distance of all privately owned vehicles in Sweden in 2022, which was 11,260 km [40]. This suggests that EV owners may be taking advantage of the relatively low driving costs of EVs. Furthermore, this study only includes models that were registered in Year 2014 or later. In general, old EVs tend to be driven shorter distances per year, as evidenced by the finding that all of the EVs registered before 2017 had driving distances shorter than 13,000 km.

Fig. 10 gives the share of driving days out of all the logging days without missing trip data for each EV. It can be seen that 89 % of the EVs are driven more frequently than once in two days, i.e., the share of driving days is higher than 50 %. The logging data also show that 74 % of the EVs are driven in a day on average (only the days during which more than 100 EVs are logged are included in the calculation).

Fig. 11 shows the daily driving distances for small-battery EVs (Fig. 11a) and large-battery EVs (Fig. 11b), as well as the cumulative share of these, with the lines showing each battery capacity group (Fig. 11c). As can be seen in Fig. 11, a and b, the peaks in the histogram are for 10–15 km (average:53 km) and 5–10 km (average:59 km) for small-battery and large-battery EVs, respectively. Fig. 11c shows that 77 % of the daily driving distances are shorter than 80 km for both battery capacity groups. Furthermore, there are only 3.5 % of days with driving distances >200 km (both groups counted), as can be seen in Fig. 11c.

Fig. 12 gives the histograms of the median (Fig. 12a, b) and maximum (Fig. 12c, d) daily driving distances of the logged EVs for the two battery capacity groups. There is only a weak dependency of the median daily driving distance on the battery capacity, with the peak at around 30 km (for small-battery EVs, 44 km; for large-battery EVs, 39 km, on average). Yet, Fig. 12, c and d shows that the maximum daily driving distances differ significantly between the small-battery EVs (average: 284 km) and large-battery EVs (average: 429 km), which is as expected. Calculations of the two-sided *p*-values of the median daily driving distance (Fig. 12 a and 12b) and max daily driving distance (Fig. 12 c and 12d) when using Mann-Whitney *U* test [41] is performed showing a result of 0.17 and 1.4e-10, respectively, which means the distribution of the median daily driving distance is similar between the battery capacity groups while the distribution of the max daily driving distance differs. These results imply that the advantage of EVs with large batteries is only occasionally exploited. According to the data, the average energy consumption for driving is 0.156 kWh/km, which is not significantly different between the battery sizes (small battery, 0.144 kWh/km; large battery, 0.162 kWh/km).

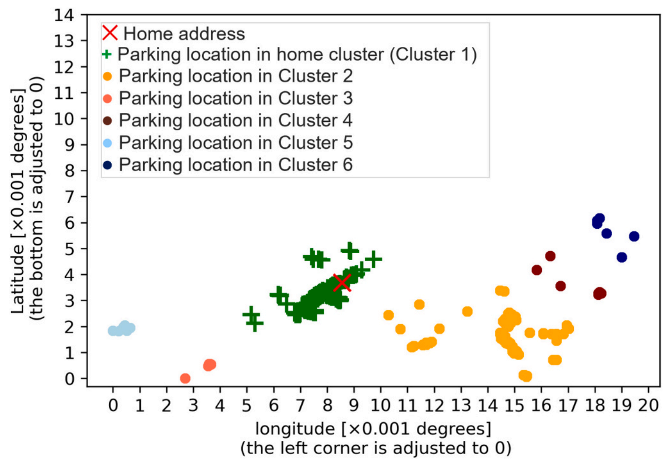

Fig. 8. Clusters of parking places and the home address for one of the EVs examined in this study. The *x*-axis and *y*-axis are longitude and latitude, respectively, with adjustment of the left-bottom point to 0 degrees, in order not to reveal the exact location of the EV owner.

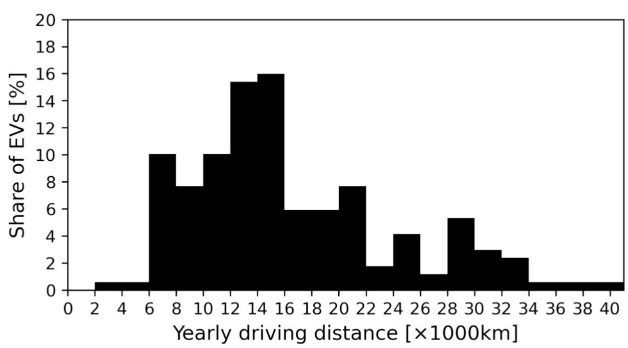

Fig. 9. Yearly driving distance. Bin width is 2000 km. Data shown are for 169 EVs.

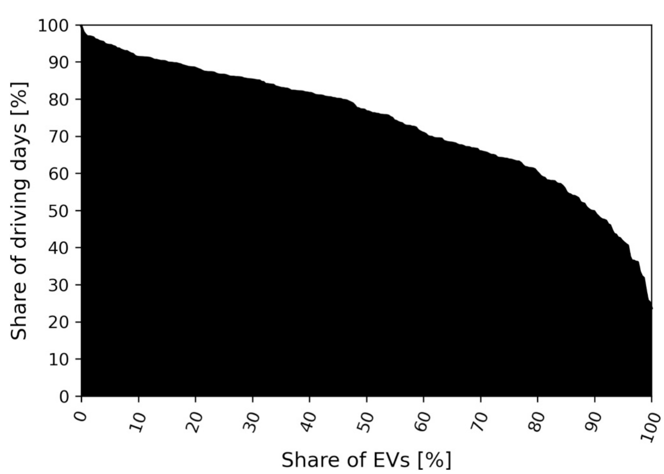

Fig. 10. Shares of driving days per logged EV in descending order. Data shown are for 289 EVs.

3.2. General parking and charging patterns

The number of hours that EVs are being parked without charging (for driving needs) and the time of the day for parking are important pieces of information for determining the potentials for flexible and smart charging. Fig. 13 shows the shares of the EVs that are parked either at the home location or at other locations, and the shares of the EVs that are charging at these two locations at each time of the day on average. As can be seen in Fig. 13, the share of EVs that are driven at a certain time of the day is small, at less than 10 %, which occurs at 16:40 h. Two small peaks can be seen, with one in the morning at around 08:00 and one in the evening at around 17:00.

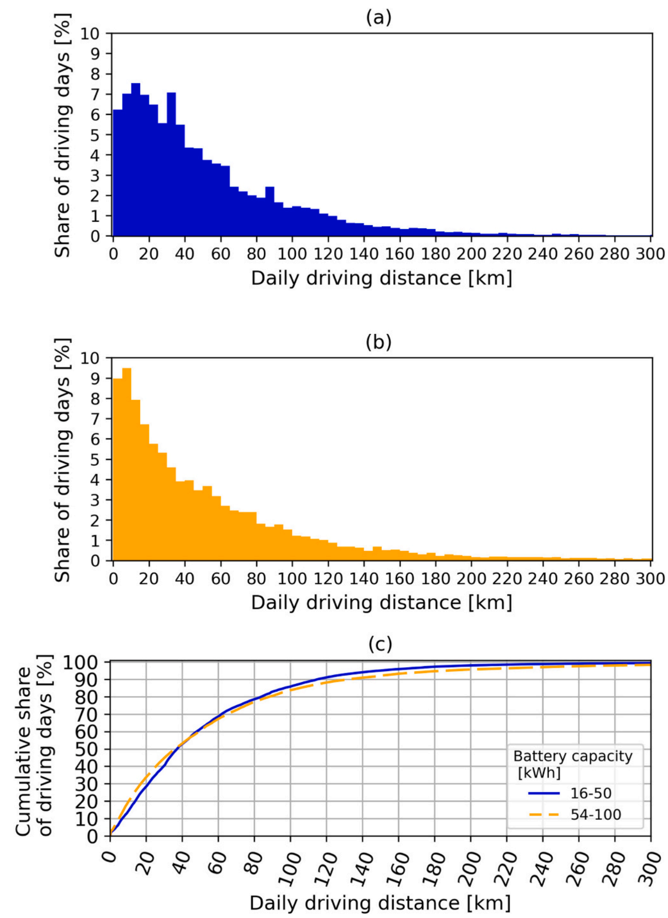

Fig. 11. Daily driving distances of the logged EVs with battery capacities of: (a) 16–50 kWh; and (b) 54–100 kWh. (c) Cumulative shares of driving days. Bin width for (a) and (b) is 5 km. Note that only the driving days are counted, i.e., the *x*-axis shows only values >0. Data shown are for 80,587 driving days by 334 EVs.

The maximum number of EVs charging at the same time is 13 % on average, which occurs at 00:10 h, i.e., just after midnight (see the sum of the red- and green-colored fields in Fig. 13). Out of all the hours logged, not more than 28 % of the EVs are charging at the same time. From Fig. 13, one can also see that the share of EVs parked at the home location without charging is large (see the orange-colored field in Fig. 13). At midnight, about 83 % of the EVs are parked at home. The share of EVs parked at home decreases from 05:00 h and reaches the lowest values between 11:00 and 15:00 h, as seen in Fig. 13. Overall, at least 50 % are parked at home during daytime, on average. At least 33 % of the fleet is parked at the home location during any of the logged hours, which occurs during daytime (12:30), and 60 % at midnight (note that only those hours during which more than 100 EVs are logged at the same time are included). Therefore, there seems to be a strong potential for flexible charging at home location, since at any point during the day a large share of the EVs is parked at home without charging. The duration of the parking without charging, together with the battery capacity, determines the theoretical potential for smart charging. The real potential for smart charging depends, of course, also on the preferences of the EV users.

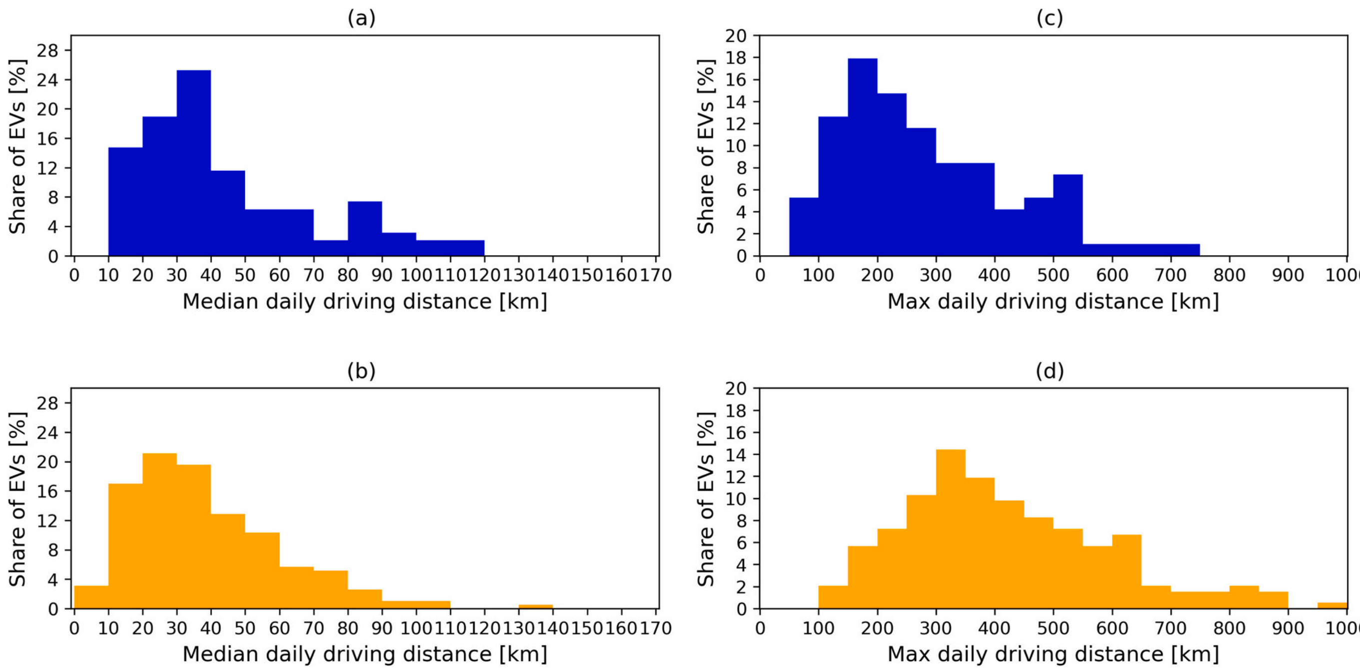

Fig. 12. Median and maximum daily driving distances of the EVs with battery capacities of (a, median; c, maximum) 16–50 kWh; and (b, median; d, maximum) 54–100 kWh. Bin widths are 10 km for (a) and (c); and 50 km for (b) and (d). Data shown are for 289 EVs.

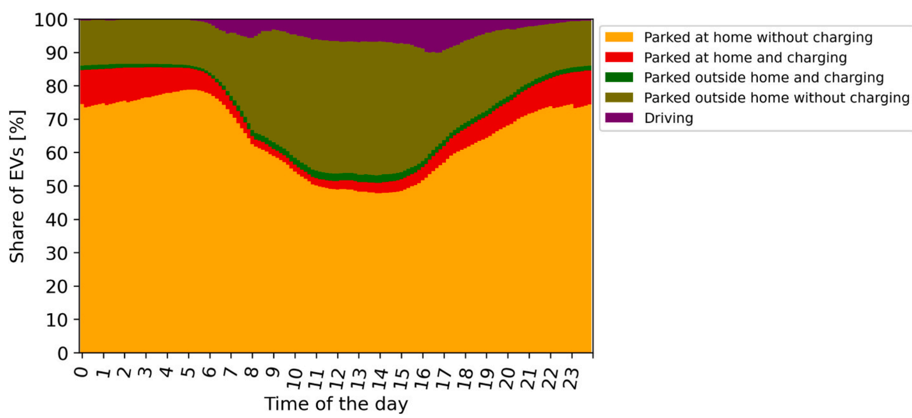

Fig. 13. The shares of EVs being parked with/without charging at the home location or at the other locations, and the shares of EVs driving at each time of the day, on average. The resolution is 10 min. Data shown are for 334 EVs.

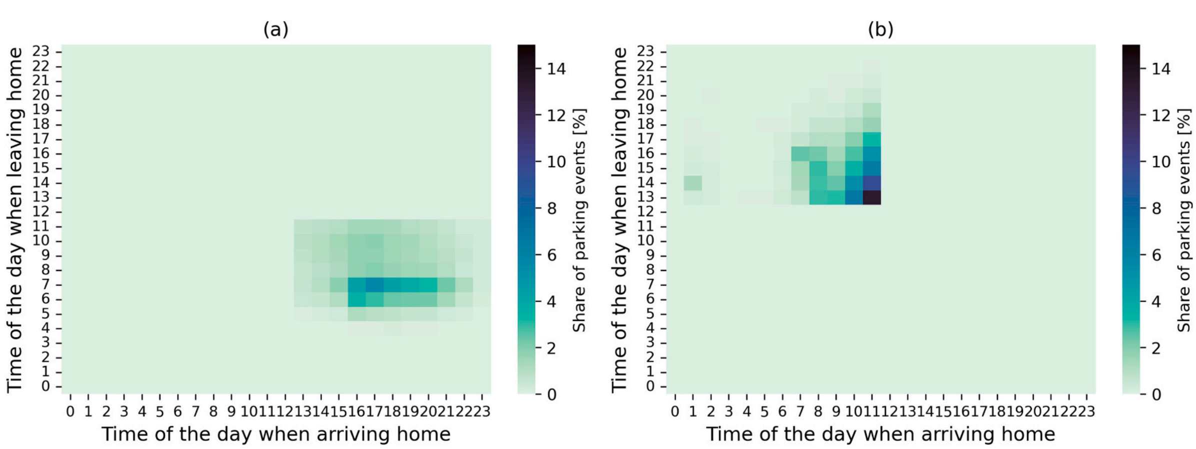

Fig. 14. Times when arriving and leaving home for: (a) night-time parking events; and (b) daytime parking events. Data shown are for: a, 37,868 parking events by 334 EVs; and b, 6673 parking events by 334 EVs.

Fig. 14 shows the time when arriving and when leaving home of a night-time (14a) and daytime (14b) parking event. As shown in Fig. 14a, the EVs are likely to arrive home in the evening around 16:00–20:00 h (with a peak at 17:00) and leave home in the morning around 06:00–07:00 h. The EVs that are parked at noon (Fig. 14b) tend to arrive home just before noon, between 10:00 and 12:00 h, and leave home again between 12:00 and 16:00 h. Note that Fig. 14 does not include parking at home that is longer than 24 h or short parking events that occur exclusively in the morning/afternoon (see Table 5 for the definition of night-time/daytime parking events).

Comparing the results depicted in Fig. 14, a and b, it can be concluded that, as expected, the night-time parking events tend to be longer (average of 14 h) than the daytime parking events (average of 5 h) at home. Furthermore, daytime parking events are shorter than the nighttime parking events at the home location, where (22 % of the daytime parking events are shorter than 3 h. EVs parked during daytime at home location have the possibility to perform other grid services on a shorter time-scale. It can also be beneficial for the grid to have vehicles parked at home, even for 3 h, as they can utilize local solar power generation. Thus, Figs. 13 and 14 show – as expected - that the potential for flexible/smart charging is significantly higher during night-time than during daytime. This is because more EVs are parked and for longer parking events during night-time. Nonetheless, the EVs parked during daytime can play an important role, such as the storage of solar energy during the daytime, and can contribute to ancillary services.

3.3. Characteristics of charging and parking at home during night-time

Among the EVs that were charged at least once at their home location, 70 % of the charged energy was charged at the home location (95 % confidence interval: [66 %, 74 %]). Furthermore, 86 % of the energy charged at home was charged during overnight parking events. Fig. 15 shows the SOC when arriving home for an overnight parking event for the two battery-capacity groups of 16–50 kWh (Fig. 15a) and 54–100 kWh (Fig. 15b). Comparing the two figures, it is clear that there is almost no difference in the results between the two battery-capacity groups, as more than half (56 %) of the trips for all EVs arriving at home for overnight parking events have an SOC of 60 % or higher.

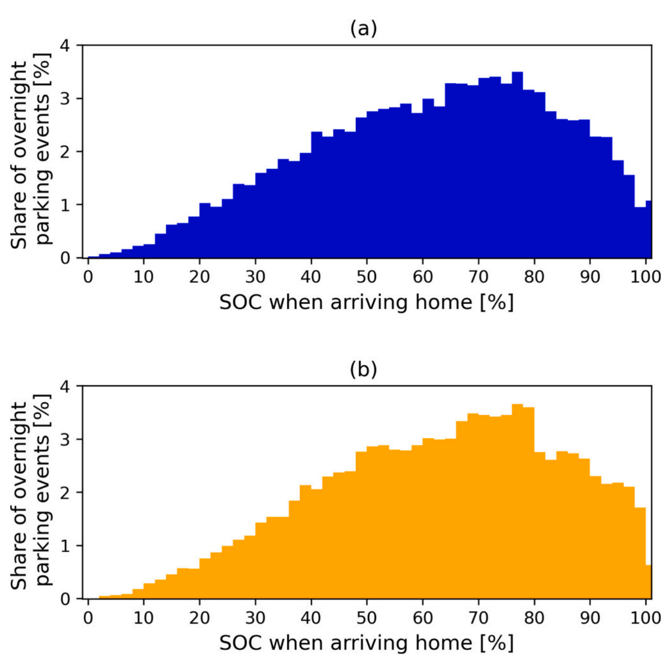

Fig. 15. SOC when arriving home for overnight parking events assuming battery capacities of: (a) 16–50 kWh; and (b) 54–100 kWh. Bin width is 2 %. Data shown are for 62,026 parking events by 334 EVs.

Yet, Fig. 16 indicates that EV owners decide to charge based on the SOC when arriving home (Fig. 16a), as well as on the expected driving distance the next driving day (Fig. 16b). As can be seen in Fig. 16a, large-battery EVs tend to be charged during fewer overnight parking events than smaller-battery EVs. For example, when the EVs have 60 % SOC, the small-battery and large-battery EVs are charged during 64 % and 34 % of the overnight parking events, respectively. It can also be noted that even if the battery is almost full (90 % SOC) when arriving home for overnight parking events, some of the EV owners tend to charge the battery (36 % and 19 % of the overnight parking events, for the small-battery and large-battery EVs, respectively). The two lines in Fig. 16a can be fitted with $y = -0.79x + 105.0$ for small battery EVs ($R^2 = 0.97$) and $y = -1.06x + 100.7$ for large battery EVs ($R^2 = 0.97$), where 10–90 % SOC and 10–80 % SOC are fitted for small and large battery EVs, respectively.

Fig. 16b shows that for the small-battery EVs, the charging probability increases when the following daily driving distance exceeds 140 km, and stabilizes at around 80 % charging probability if driving farther than 140 km the next driving day. The charging probability for large-battery EVs is instead 70 % when the following daily driving distance exceeds 180 km. The two lines in Fig. 16b can be fitted with $y = 0.34x + 37.1$ for small battery EVs ($R^2 = 0.96$) and $y = 0.25x + 21.5$ for large battery EVs ($R^2 = 0.98$), where 10–150 km and 10–190 km next daily driving distance are fitted for small and large battery EVs, respectively.

Fig. 17 shows the charging probability outside the home location for different daily driving distances (only the first driving days after an overnight charging event are included). As shown in Fig. 17, the charging probability outside the home increases steeply for daily driving distances that exceed 120 km for the small-battery EVs and 180 km for the large-battery EVs.

The differences in charging probabilities between the large-battery and small-battery EVs in Fig. 17 and the similarity in the SOC when arriving home (Fig. 15) result in a difference in the frequency of overnight charging events. Fig. 18 shows the number of driving days for two overnight charging events. On average, the large-battery EVs spend 2.5 driving days between two overnight home charging events, as compared with 1.6 driving days for the small-battery EVs. About 50 % of the overnight charging events (the two battery groups together) are made only one driving day after the last time that the EVs were charged during overnight parking events at the home location.

Fig. 19 shows the SOC at the completion of the overnight charging events. It is evident that most of the charging events are continued until the SOC reaches almost 100 %. However, there are sharp peaks at 80 % and 90 %, especially for the large-battery EVs. Most likely, the large-battery EVs use a function built into the car or charger that automatically stops charging at 80 % or 90 % SOC level, so as to avoid battery degradation. Some of the owners of large-battery EVs take advantage of the opportunity to decide when to charge, as well as the opportunity to stop charging at a lower SOC in daily life, possibly to prolong the lifetime of the battery.

3.4. Flexibility of charging time at home during night-time

Fig. 20 shows the duration of overnight parking events at home. It is clear that there is a large spread in the durations of the parking events, with the most-frequent parking duration being 14 h. 94 % of the overnight parking events last for 10 h or longer, for obvious reasons. Fig. 21 shows the duration of charging events during the overnight parking events for the small-battery EVs (Fig. 21a) and large-battery EVs (Fig. 21b), and for the 3–4 kW (Fig. 21c) and the 9–10 kW (Fig. 21d) maximum charging powers for the large-battery EVs. As can be seen in Fig. 21, a and b, the most-frequent charging duration differs slightly between the small-battery and large-battery EVs. Since many EVs are parked at the home location for a long time without charging, there appears to be a large potential for flexibility in charging time. The

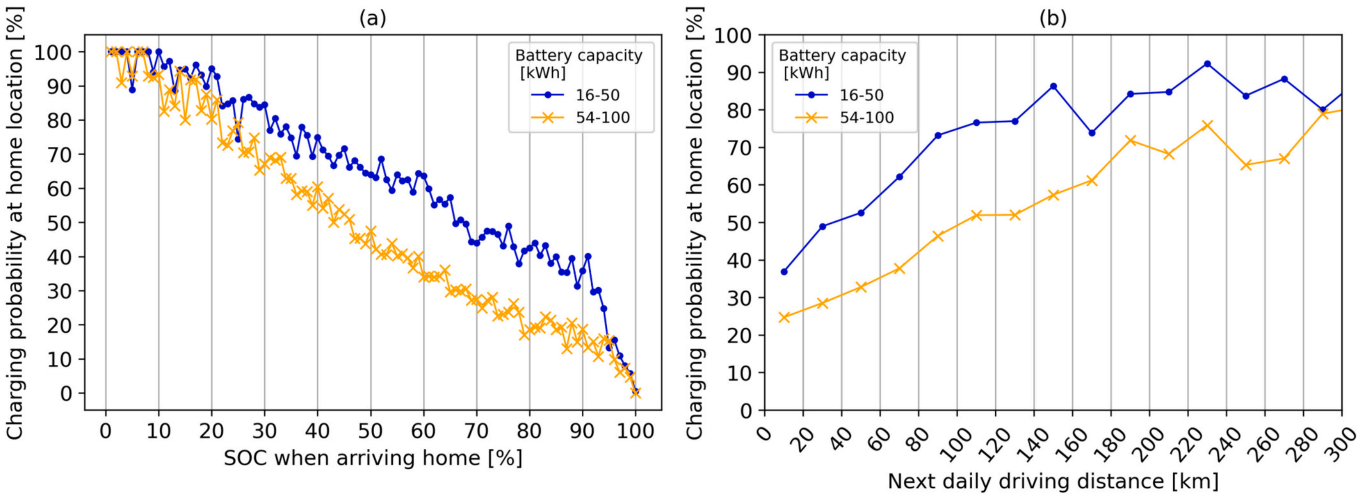

Fig. 16. Charging probability at home location in overnight charging events versus (a) SOC when arriving home and (b) next daily driving distance. Data shown are for: a, 46,599 parking events by 257 EVs; and b, 50,712 parking events by 253 EVs.

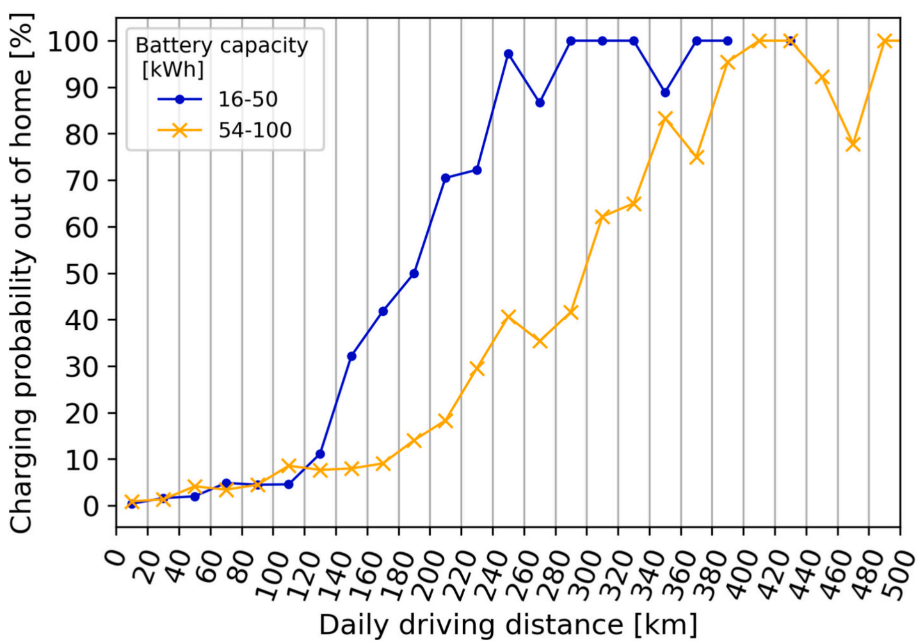

Fig. 17. Charging probabilities outside home location for different daily driving distances (only the first driving days after an overnight charging event are included). Data shown are for 21,132 driving days by 253 EVs.

possibility to shift charging in time also depends on the maximum charging powers of the chargers at the home locations, as can be seen by comparing Fig. 21, c and d. As expected, a higher maximum charging power gives a shorter average charging duration. The histogram for the EVs that have a maximum charging power of 3–4 kW shows a broad distribution of charging duration (Fig. 21c), while that for the EVs with maximum charging power of 9–10 kW shows a peak at around 4 h (Fig. 21d). The median charging durations are 9 h and 4 h for the maximum charging powers of 3–4 kW and 9–10 kW, respectively.

Fig. 22 shows the elapsed time from arriving home to the beginning of charging, divided between apartments and detached houses. For the EV owners living in apartments, 77 % started to charge within 1 h after returning home (Fig. 22), while this was the case for 50 % of those living in detached houses. This pattern is also seen in Fig. 23, where the distribution of the starting time for charging is skewed towards later times for those living in detached houses, as compared with the distribution for those living in apartments. In addition, there are concentrations of starting charging at exactly 22:00, 23:00, and 00:00 h, indicating that the start time for automatic charging is a direct response to electricity price signals or is indirectly triggered by some App or timer. As can be seen in Fig. 23, these peaks are more pronounced for the EV owners living in detached houses. This is likely to be because EV owners living in detached houses are more likely to have a flexible electricity price contract than EV owners living in multifamily buildings.

4. Discussion

The results of the analyses of the driving and charging patterns of the logged EVs show that there is strong potential for shifting charging in time, especially during night-time at home. This can be concluded from the high number of parked EVs, the high SOC when arriving home, and the short time needed for charging compared to the duration of parking. The dataset collected and analyzed in this study provides the information required to clarify the driving and charging patterns of currently

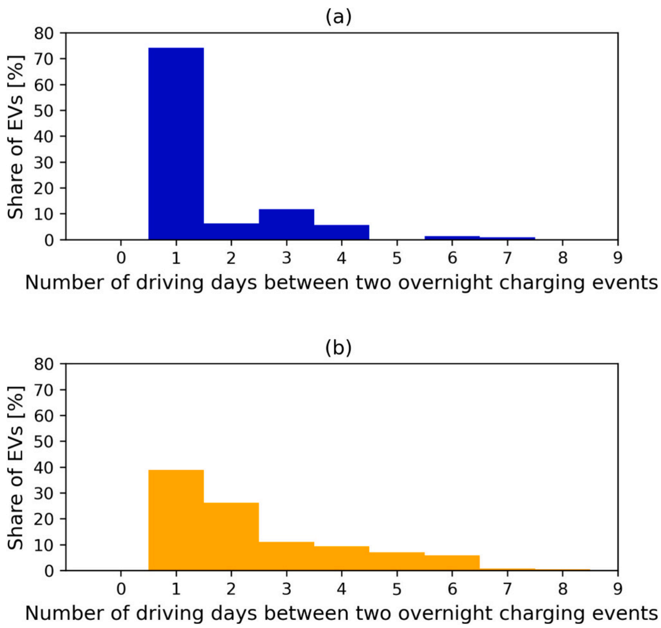

Fig. 18. Numbers of driving days between two overnight charging events assuming battery capacities of (a) 16–50 kWh and (b) 54–100 kWh when the EVs are not charged at any location between the overnight charging events. Bin width is 1. Data shown are for: 14,414 pairs of charging events by 253 EVs.

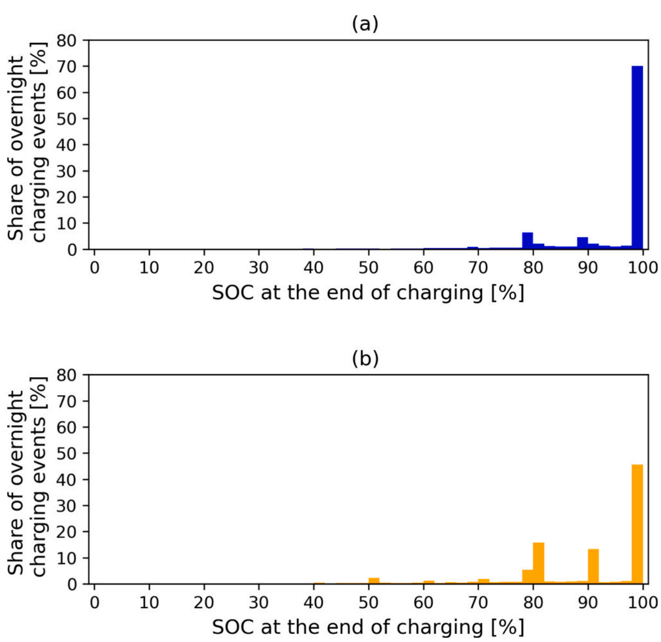

Fig. 19. SOC at the end of overnight charging events assuming battery capacities of (a) 16–50 kWh; and (b) 54–100 kWh. Bin width is 2 %. Data shown are for: 24,751 charging events by 334 EVs.

operated EVs in Sweden.

Compared to previous studies, the yearly driving distance for EVs calculated in the present work (16,530 km) is slightly shorter than that based on the driving patterns of ICVs in Sweden (17,400 km) assessed by Taljegard et al. [10], while the average yearly driving distance for privately owned vehicles in Sweden is 11,260 km [40]. Taljegard et al. [10] have pointed out that their dataset includes a larger share of diesel cars than is the average for Sweden. The EVs in the present study tend to drive longer distances than gasoline-fueled cars but shorter distances than diesel-fueled cars. This implies that EV owners are early adopters

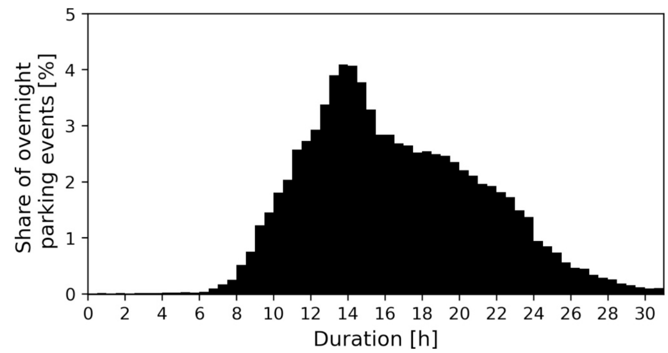

Fig. 20. Durations of overnight parking events at the home location. Bin width is 30 min. Data shown are for: 66,375 parking events by 334 EVs.

who want to gain greater economic benefits from buying an electric car. However, the owners of diesel cars want EVs with large batteries, as the results show that the EVs with battery capacities >77 kWh are driven 20,574 km per year on average. According to Smart et al. [20], the annual driving distance of a Nissan LEAF (24 kWh) in the US is 15,600 km, while the national average driving distance for all vehicles in the US is 18,300 km. This implies that the driving range of an EV with a 24-kWh battery is not sufficient to fulfill the requirements of the average driving pattern in the US. Focusing on EVs with battery capacities of up to 30 kWh in the present study, the average yearly driving distance is 11,138 km. Although this is a much shorter distance than the average for all EVs (16,530 km) logged in this study, it is similar to the average for all privately owned vehicles in Sweden (11,260 km).

The average daily driving distance of the participants in this study (small-battery EVs: 53 km, large battery EVs: 59 km, on average) is close to that of the averages in European countries. Alemanno et al. [6] have reported a similar average driving distance for Italy, France and Germany. Moreover, the large-battery EVs in this study show an average daily driving distance that is close to the Swedish ICV data (58 km) used in the study of Taljegard et al. [10], which are based on the driving patterns measured by Karlsson [12]. However, the peaks of the histograms in Fig. 11a (small-battery EVs: 10–15 km) and 11b (large-battery EVs: 5–10 km) are similar to the results (around 10 km) obtained from the analyses of the data for the 24-kWh EVs (Nissan LEAF) in the US by Suzuki et al. [21]. The present study shows that 80 % of the daily driving distances are shorter than 80 km, similar to what is seen in the results of Suzuki et al. [21]. Although the average daily driving distance is similar to those reported in some of the previous studies, the present study reveals that the median daily driving distance for each EV is similar for the two battery capacity groups investigated, while the EVs with larger battery capacities show a longer average maximum driving distance.

In terms of the share of parked and driving EVs, the results of this study show that 10 % of EVs are driven at most at the same time at 16:40 h on average, while Karlsson et al. [12] have shown that 7 % of the logged ICVs are driven at most at 17:00 h based on the data on ICVs in Sweden. This result and the shape of the graph for the share of cars being driven is similar to the graph with another peak share of cars being driven in the morning (this study: 6 % at 07:50; Karlsson et al. [12]: 5 % at 08:00). The share of cars being driven is slightly higher for EVs than for ICVs, probably because the EV owners drive on more days, albeit for shorter distances.

The probability of charging at home in this study is similar to the plug-in probability at home described in Suzuki et al. [21]. Suzuki et al. [21] have reported a plug-in probability of 30 % with 60 % SOC when arriving at home, while the charging probability in the present study for small-battery EVs is 64 % for the same SOC. This is likely because only overnight parking events are counted in the present study. When calculated for all parking events at home, the charging probability becomes 45 %. According to the analysis conducted by Dodson et al. [22],

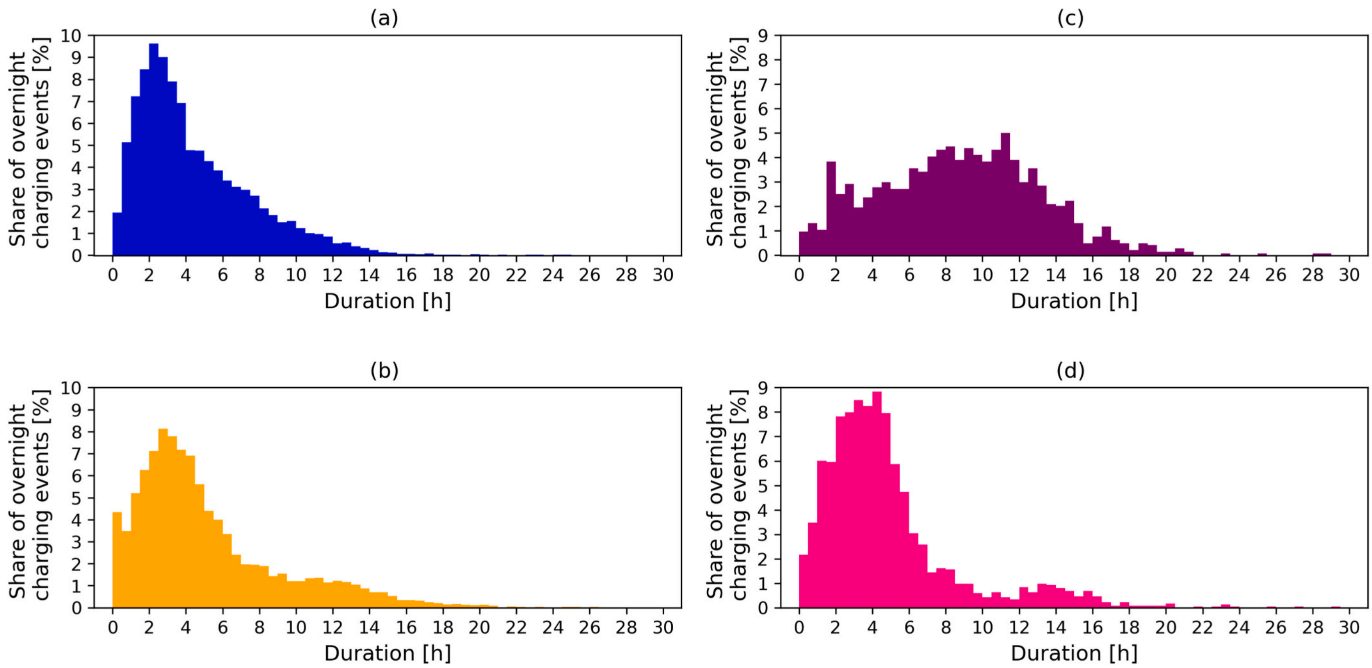

Fig. 21. Durations of overnight charging events at home location for battery capacities (a) 16–50 kWh and (b) 54–100 kWh, and for maximum charging powers of (c) 3–4 kW and (d) 9–10 kW for the large-battery EVs (54–100 kWh). Bin width is 30 min. Data shown are for: a and b, 21,769 charging events by 283 EVs; c and d, 10,499 charging events by 62 EVs.

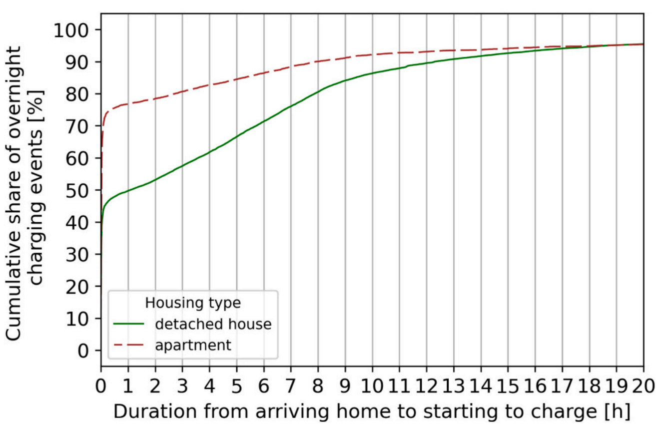

Fig. 22. Elapsed time from arriving home to starting to charge by housing type. Data shown are for: 21,784 charging events by 283 EVs.

for EVs in the UK the peak demand for charging is seen at 19:00–20:00 h, whereas the highest number of EVs charging in the present study is at around 00:10 h (13% for the sum of the red and green areas in Fig. 13). This difference is possibly because more EV owners in Sweden in 2022–2024 shifted their charging time than EV owners in the UK in 2017–2018, as can be seen in Figs. 22 and 23.

As mentioned above, the yearly driving distance results imply that EV owners are early adopters (the share of EVs in Swedish traffic was 5.9 % in 2023) who want to get as much out of their cars as possible, and that it is more economically beneficial for people who are driving longer yearly distances to buy an EV. Yet, it could also be because the driving cost per kilometer is low and people tend to drive more. The share of EVs in Sweden is still small (5.9 %), but the share of new sales was 39 % in 2023 [42]. Since the EV share is increasing, the driving and charging patterns should be monitored to allow the design and dimensioning of infrastructure, so that EV market diffusion is not hindered by inadequate infrastructure.

The share of EVs in new car sales in Sweden was the third highest

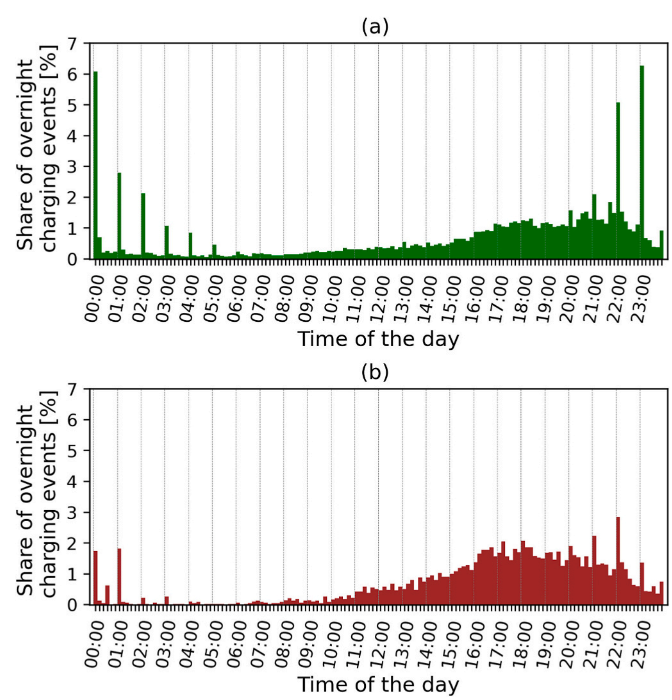

Fig. 23. Time of the day when charging starts at an overnight charging event for EV owners: (a) living in detached houses; and (b) living in apartments. Bin width is 10 min. Data shown are for: 24,766 charging events by 334 EVs.

among the EU-27 countries [42], which means more non-early adopters are starting to purchase EVs in Sweden compared to many other EU countries. Many of the participants in this study use their EV to visit their vacation houses (36 %) which might differentiate the driving and charging patterns from the other countries. As mentioned earlier, the driving and charging patterns differ between countries, e.g., the yearly driving distance differs between Sweden and the US [20]. Another example is the difference in charging demand between Sweden and the UK [22]. However, there are also similarities such as daily driving distance in Sweden and the US [21]. The yearly driving distance on average for all vehicles in Sweden (11,260 km) is similar to the yearly driving distance in Norway (11,097 km), Netherlands (11,015 km) and Croatia (11,733 km), while it is significantly different from Austria (12,600 km), Belgium (15,893 km), Denmark (14,585 km), Finland (14,000 km), France (10,830 km) and Latvia (14,690 km) [43]. The driving and charging patterns depend on many things, such as the lifestyle, electricity price contract, access to charging infrastructure, working hours, etc. Thus, it is important to monitor the driving and charging patterns in each country and from many EV users to understand the need for charging infrastructure, as well as understand how EV charging might impact the grid.

Future work will analyze a survey sent out to the EV owners participating in this study. The survey will help further define the attributes of the participants and their preferences for smart charging. An analysis of attribute could point at different reasons for certain driving and charging patterns. Yet, also the present results in this paper provide such information. For example, the results show that EV owners living in detached houses tend to delay charging, but future analysis is needed to also correlate with, e.g., type of electricity contract, electricity spot price and access to charging infrastructure. In the present study, charging at the home location was in focus. However, a more-extensive geographic analysis that includes also charging at workplace, summerhouse locations and other locations, as well as, analysis of differences of driving and charging patterns between city sizes (i.e. urban cities, small towns or countryside) is required to clarify the potential for flexible charging and the need for charging infrastructure. However, such analysis is considered outside the scope of this paper. Further analysis is also needed to understand how driving and charging patterns might differ between weekdays and between different seasons. This is important in order to understand when and where to build charging infrastructure, e.g., from the perspective of policy. Yet, further analysis will require a comprehensive analysis which is out of scope of this work. The results presented in this study show that some of the owners of large-battery EVs take advantage of the opportunity to end the charging event at a lower SOC than those with a smaller battery, with the reason possibly being that they want to prolong the lifetime of the battery. Yet, further analysis is outside the scope of this work. The driving and charging patterns recorded in this study will also be useful for simulating the electricity grid, so as to determine how EV charging affects the current grid.

5. Conclusions

The results obtained from analyzing the charging and driving patterns of 334 GPS-logged EVs in Sweden show that there is strong potential for the total electricity load from EVs to be flexible in time, i.e., to allow smart charging, including V2G. This is the case because:

- For more than half (56 %) of the overnight parking events, the EVs arrive home with a SOC of 60 % or higher. The EV owners charge during overnight parking events (to fulfill their driving needs) on average every 2.5 driving days (for a large battery capacity) or every 1.6 driving days (for a small battery capacity).
- The most-frequent overnight parking duration at home is 14 h, which is four-times longer than the most-frequent overnight charging duration at home for logged EVs, indicating a large potential for moving charging in time. Obviously, the duration of charging also depends on the power of the chargers at home. With a 3–4 kW maximum charging power, the median duration of charging per day is 4 h, while with a maximum charging power of 9–10 kW the median charging duration is 9 h.
- The maximum share of the investigated EV fleet charging simultaneously is 13 % on average, which occurs at 00:10 over the logged period. This small share is because the battery capacity is large in relation to the average daily driving distance. This implies that there is a large potential for using the EVs in smart charging strategies that shift the load in time.
- The analysis shows that the EV owners who are living in a detached house avoid charging immediately when arriving home for 50 % of the overnight charging events, which is 27 percentage points higher than for those who live in an apartment. This is probably because the owners of detached houses tend to have hourly electricity contracts. This indicates a willingness among EV owners to move charging in time, given an economic incentive.

Furthermore, around 70 % of the charging energy is charged at the home location, and 86 % of the energy is charged during overnight parking events. The results also show that the median daily driving distance of each EV is weakly dependent upon the battery capacity, while the longest daily driving distance of each EV is 284 km for the EVs with battery capacities of up to 50 kWh (small-battery EVs) and 429 km for EVs with larger battery capacities. This suggests that the advantage of using EVs with large batteries for long trips is only occasionally exploited, although the owners of EVs with larger batteries have more flexibility in choosing when they charge their vehicles, e.g., the probability of charging when they arrive home with 60 % SOC is 1.9-times higher for large-battery EVs than for small-battery EVs.

In terms of future work, the studies will be based on the answers to surveys received from the EV owners regarding the context of their EV ownership. We will also analyze charging locations other than the home location as well as analyze temporal differences of driving and charging patterns such as in different seasons. The analysis will be extended to analysis of charging patterns regarding battery life and charging cost.

CRediT authorship contribution statement

Yuki Kobayashi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Maria Taljegard:** Writing – review & editing, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Filip Johnsson:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A.

Logging methods.

Odometer values are stored according to storing Method 1 (Section 2.1) in this study. Fig. A1 shows an example of the stored odometer values for one vehicle over a period of 40 min. The odometer values are stored every 1 km for this vehicle. All data-points that are measured will be stored.

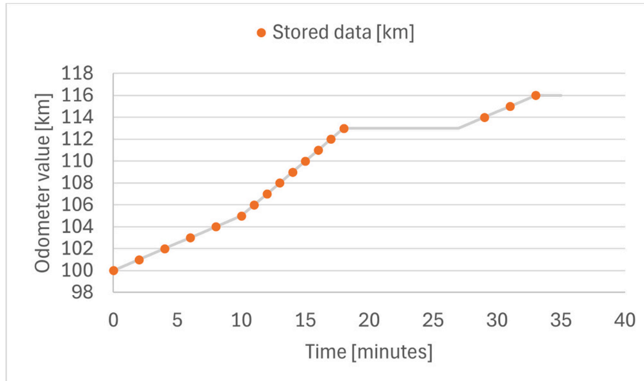

Fig. A1. Example of stored odometer values for one vehicle during 40 min. Storage of data is according to Method 1 in this study.

Method 2 for storing data entails the Ramer-Douglas-Peucker algorithm. The process of storing data according to Method 2 is described in Fig. A2, which depicts the charging power for 40 min for one vehicle. The first step (Fig. A2a) is to draw a line from logging data-points A to B (red line). In Fig. A2a, there are several measured data-points in between points A and B. A measured data-point that is most-distant from the line AB (green arrow in Fig. A2a indicates the distance), i.e., point A′, is recorded if the distance to the red line is longer than a certain threshold value. In the example in Fig. A2, the threshold value is 1 kW. The second step is to draw a line from A′ to B (Fig. A2b) and from A′ to A (Fig. A2c) and then repeat the same process. In Fig. A2b, another point A″ (most-distant from the line A′B) can be recorded if the distance (green arrow) from the red line A′ to B is longer than the threshold value. However, no such point can be found in Fig. A2c, which means that no data are stored between A′ and A. These steps are repeated until the distance from the line to the most-distant point is lower than the threshold value. Fig. A2d shows which data-points were stored according to the example in Fig. A2

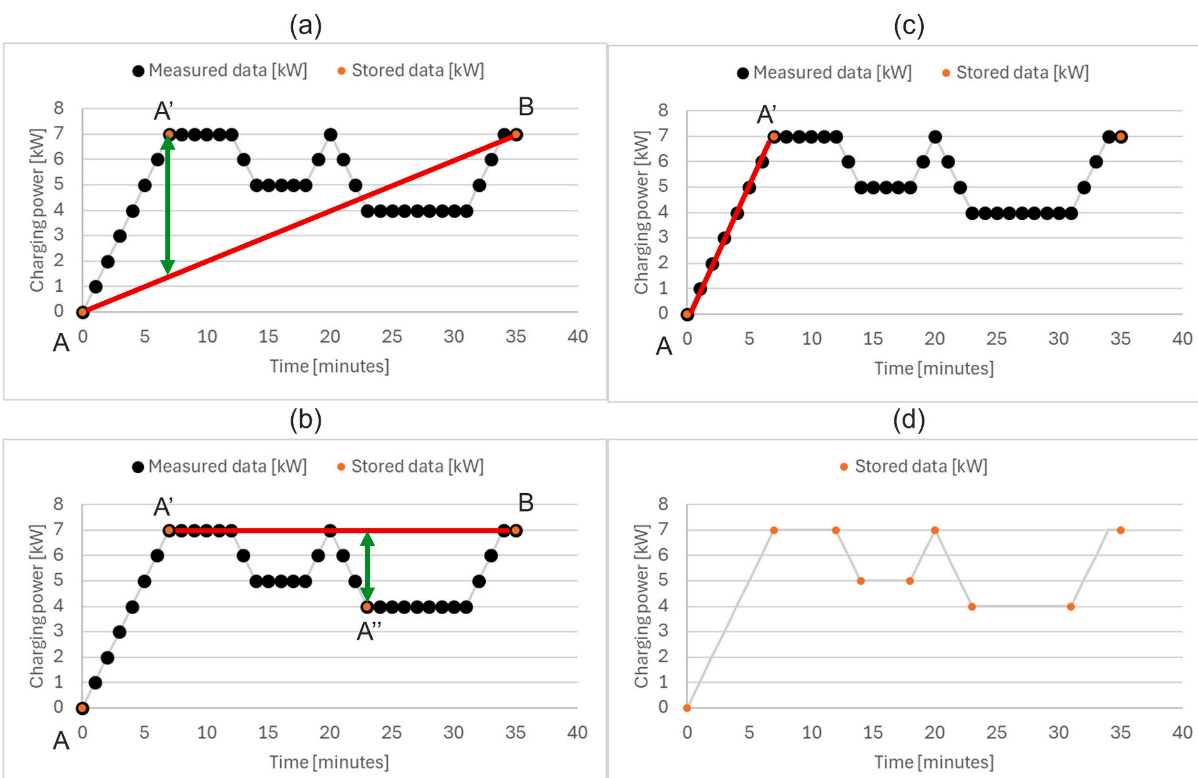

Fig. A2. The process for selecting stored data-points using Method 2. This is an example using the charging power for one vehicle during 40 min. The green arrows indicate the distance from the red line to the most-distant measurement point. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Appendix B.

Number of EVs in the different phases.

Table B1
Number of participants in the pilot phase.

	Total	Detached houses			Apartment buildings		
		Non-urban area	Small town	Large urban area	Non-urban area	Small town	Large urban area
EVs in the sampling frame (that meet the eligibility criteria)	35,209	5620	13,510	10,173	0	988	4918
Invited EVs (randomly selected from the sampling frame)	300	60	60	60	0	60	60
EV owners who accepted the invitation	34	13	4	5	0	7	5
Participants included in this study	23	10	3	2	0	4	4

Table B2
Number of participants in the second phase.

	Total	Detached houses			Apartment buildings		
		Non-urban area	Small town	Large urban area	Non-urban area	Small town	Large urban area
EVs in the sampling frame (that meet the eligibility criteria)	33,260	5337	12,869	9538	27	899	4590
Invited EVs (randomly selected from the sampling frame)	4449	336	1540	911	27	737	898
EV owners who accepted the invitation	340	50	140	79	3	70	73
Participants included in this study	250	27	78	52	2	49	42

Table B3
Number of participants in the third phase.

	Total	Detached houses			Apartment buildings		
		Non-urban area	Small town	Large urban area	Non-urban area	Small town	Large urban area
EVs in the sampling frame (that meet the eligibility criteria)	55,217	8917	21,439	15,488	65	1290	8018
Invited EVs (randomly selected from the sampling frame)	2200	427	427	427	65	427	427
EV owners who accepted the invitation	106	19	20	18	4	25	20
Participants included in this study	61	11	12	9	2	16	11

Appendix C.

Method to quantify missing data.

Eqs. C1 to C16 describe how the share of missing data has been quantified in this study. Identifications of the missing data periods are described below.

Table C1
Parameters and sets in the equations.

Sets	
N^{odo}	Recorded data-points of odometer values
N^{soc}	Recorded data-points of SOC
N^{trip}	Recorded data-points of trip data
N^{status}	Recorded data-points of status data
N^{event}	Recorded data-points of trip or charge event data
$N^{socuppark}$	Recorded data-points of parking events with SOC increased by more than 2 %
$N^{socmisstrip}$	Recorded data-points of trip event without recording SOC starts or ends
$N^{odobetweentrip}$	Recorded data-points of odometer values between trip events
$M^{missall}$	Data-missing periods (no data are recorded)
$M^{misstrip}$	Periods when trip events are missing
$M^{misscharge}$	Periods when charging events are missing
X	Start or end of event data
Parameters	
$Odo_{n^{odo}}$	Odometer values at recorded data-point n^{odo}
$SOC_{n^{soc}}$	SOC at recorded data-point n^{soc}
$SOC^{X}_{n^{event}}$	SOC when a trip or charge event starts or ends at recorded data-point n^{event}
$SOC^{X}_{n^{socuppark}}$	SOC when a parking event with SOC increased by more than 2 % starts or ends at recorded data-point $n^{socuppark}$
$ODO^{X}_{n^{trip}}$	Odometer values when a trip event starts or ends at recorded data-point n^{trip}
$ODO^{X}_{n^{misstrip}}$	Odometer values when periods when trip events are missing starts or ends
ODO^{X}	Odometer values when the logging period starts or ends
$t^{odo}_{n^{odo}}$	Time for odometer values at recorded data-point n^{odo}

(continued on next page)

Table C1 (*continued*)

Sets	
$t^{soc}_{n^{soc}}$	Time for SOC at recorded data-point n^{soc}
$Sumdist_{n^{odo}}$	Total driving distance obtained from trip data during all the trip events between two odometer values at recorded data-point $n^{odo}-1$ and data-point n^{odo}
$Trip^{X}_{n^{trip}}$	Time when a trip event at recorded data-point n^{trip} starts or ends
$Trip^{X}_{n^{socmisstrip}}$	Time when a trip event data at recorded data-point $n^{socmisstrip}$ starts or ends without recording SOC during the event
$Event^{X}_{n^{event}}$	Time when trip or charging event starts or ends at recorded data point n^{event}
T^{X}	Time when logging period of the EV starts or ends
$Missall^{X}_{n^{missall}}$	Time when data-missing periods (no data are recorded) start or end at recorded data-point $n^{missall}$
$Misscharge^{X}_{n^{misscharge}}$	Time when periods during which charging events are missing start or end at recorded data-point $n^{misscharge}$.

Periods when all data are missing

Periods when all data are missing are defined as Eqs. C1 to C4.

- If the difference between two recorded odometer values ($ODO_{n^{odo}}$) is larger than the total driving distance obtained from trip data during all the trip events between the same two odometer values (data-point $n^{odo}-1$ and data-point n^{odo}) when adding a threshold (10 km), as in Eq. (C1):

$$ODO_{n^{odo}} - ODO_{n^{odo}-1} > Sumdist_{n^{odo}} + 10km \forall n^{odo} \in N^{odo} \tag{C1}$$

- And if the absolute difference between two recorded values of SOC is larger than the threshold (2 %), as in Eq. (C2):

$$|SOC_{n^{soc}} - SOC_{n^{soc}-1}| > 2\% \forall n^{soc} \in N^{soc} \tag{C2}$$

- And if no data are recorded.
- Only periods of missing status data longer than 1 h are taken into account, as shown in Eq. (C3), in order to avoid defining the periods between status data during the same trip or charging event as missing periods.

$$Missall^{end}_{n^{missall}} - Missall^{start}_{n^{missall}} > 1hour \forall n^{missall} \in M^{missall} \tag{C3}$$

The missing rate for all data is calculated in Eq. (C4) as the ratio of the total duration of the periods when all data are missing against the duration of total logging period.

$$\sum_{n^{missall} \in N^{missall}} \left(Missall^{end}_{n^{missall}} - Missall^{start}_{n^{missall}}\right) / \left(T^{end} - T^{start}\right) \times 100 \tag{C4}$$

Trip data are missing while status data are recorded

The cases in which trip data are missing while status data are recorded are defined as follows:

- If the difference in odometer values between two trip events is longer than 10 km, as expressed in Eq. (C5):

$$ODO^{start}_{n^{trip}} - ODO^{end}_{n^{trip}-1} > 10km \forall n^{trip} \in N^{trip} \tag{C5}$$

- The interval odometer values are always shorter than 10 km between two trip events, as in Eq. C6:

$$\max_{n^{odo} \in N^{odobetweentrip}} \left(ODO_{n^{odo}} - ODO_{n^{odo}-1}\right) \leq 10km \tag{C6}$$

where n^{odo} satisfies Eq. (C7):

$$Trip^{end}_{n^{trip}-1} < t^{odo}_{n^{odo}-1} < t^{odo}_{n^{odo}} < Trip^{start}_{n^{trip}} \forall n^{trip} \in N^{trip}, n^{odo} \in N^{odo} \tag{C7}$$

The missing rate of trip data is calculated based on the difference in odometer values, as in Eq. (C8):

$$\sum_{n^{misstrip} \in M^{misstrip}} \left(ODO^{end}_{n^{misstrip}} - ODO^{start}_{n^{misstrip}-1}\right) / \left(ODO^{end} - ODO^{start}\right) \times 100 \tag{C8}$$

Charging data are missing

The period during which charging data are missing is defined as follows:

- The difference in SOC from the previous event (trip or charge) to the next event (trip or charge) is higher than the threshold (2%), as in Eq. (C9):

$$SOC^{start}_{n^{event}} - SOC^{end}_{n^{event}-1} \geq 2\% \forall n^{event} \in N^{event} \tag{C9}$$

- The parking events in which the event n^{event} shown in Eq. (C9) are regarded as the periods for which charging data are missing, i.e., the period including missing charging data starts at the end of the trip events, as seen in Eq. (C10):

$$Misscharge^{start}_{n^{misscharge}} = trip^{end}_{n^{trip}-1} \forall n^{trip} \in N^{trip}, n^{misscharge} \in M^{misscharge} \tag{C10}$$

- And it ends at the beginning of the next trip events, as in Eq. (C11):

$$Misscharge^{end}_{n^{misscharge}} = trip^{start}_{n^{trip}} \forall n^{trip} \in N^{trip}, n^{misscharge} \in M^{misscharge} \tag{C11}$$

- Where these trip events ($trip^{end}_{n^{trip}-1}$ and $trip^{start}_{n^{trip}}$) satisfy Eq. (C12):

$$trip^{end}_{n^{trip}-1} \leq Event^{start}_{n^{event}} \leq Event^{end}_{n^{event}} \leq trip^{start}_{n^{trip}} \forall n^{trip} \in N^{trip}, n^{event} \in N^{event} \tag{C12}$$

To evaluate the missing rate of the charging data, this number of parking events is compared with the number of parking events with SOC increased by more than 2%, $N^{socuppark}$, i.e., the parking events likely to be associated with charging events, as defined by the parking events in Eq. (C13):

$$SOC^{end}_{n^{socuppark}} - SOC^{start}_{n^{socuppark}-1} \geq 2\% \forall n^{socuppark} \in N^{socuppark} \tag{C13}$$

The rate of missing data is calculated using the number of parking events with a difference in SOC increased by more than 2% between events divided by the number of parking events with SOC increased by more than 2%, as expressed in Eq. (C14):

$$count\left(M^{misscharge}\right)/count\left(N^{socuppark}\right) \times 100 \tag{C14}$$

The other parameters of status data are missing

The completeness of parameters other than charging data in the status data are evaluated using the duration of the recorded trip events or charging events during which the data are recorded. Eqs. (C15) and (C16) show the completeness of the SOC data during trip events as an example.

If no SOC is recorded during a trip event, the SOC is regarded as missing, as in (Eq. C15):

$$t^{soc}_{n^{soc}-1} < Trip^{start}_{n^{socmisstrip}} < Trip^{end}_{n^{socmisstrip}} < t^{soc}_{n^{soc}} \forall n^{soc} \in N^{soc}, n^{socmisstrip} \in N^{socmisstrip} \tag{C15}$$

The missing rate of SOC data during trip events is calculated using the duration of trip events without SOC divided by the duration of trip events, as in Eq. (C16):

$$\sum_{n^{socmisstrip} \in N^{socmisstrip}} \left(Trip^{end}_{n^{socmisstrip}} - Trip^{start}_{n^{socmisstrip}}\right) / \sum_{n^{trip} \in N^{trip}} \left(Trip^{end}_{n^{trip}} - Trip^{start}_{n^{trip}}\right) \times 100 \tag{C16}$$

Appendix D.

Age and gender distribution of the participants.

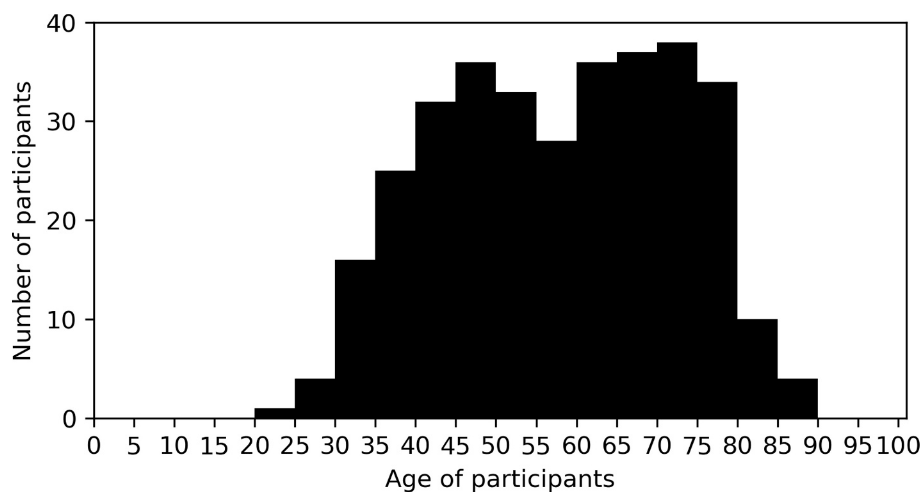

Fig. D1. The age distribution of the participants in this study. Bin width is 5 years.

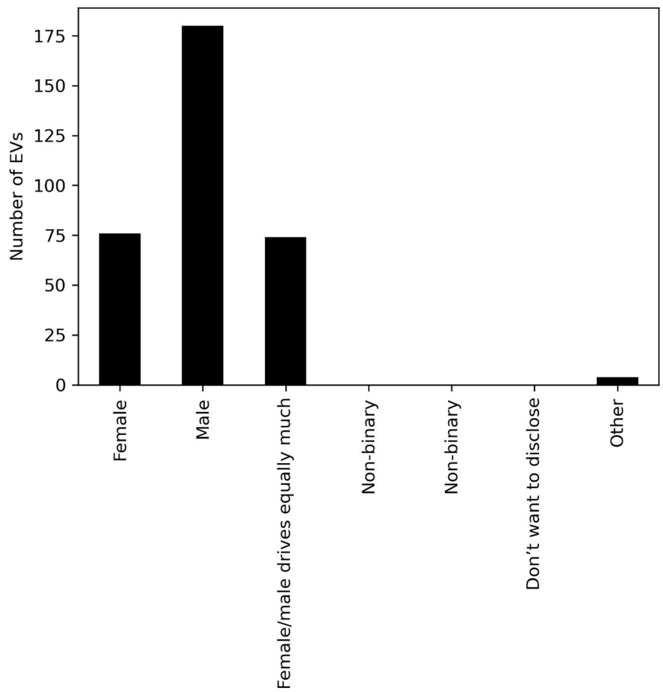

Fig. D2. The gender of the driver using the EV most of the time in this study according to a survey sent out to the participants.

Appendix E.

EV models with large missing rates.

Table E1
Number of EVs with a missing data rate higher than 20 % by model and parameter. Note that e.g., the model name "Nissan Leaf" includes every battery size of Nissan Leaf as well as Nissan Leaf e + .

	Total number of EVs	All data	Trip event	Start/end of a charging event	Odometer values	SOC during trip event	Energy charged to battery during charging	SOC during charging event	Energy demand for driving	Charging power
AUDI E TRON	1	0	0	0	1	1	0	1	0	0
BMW I3	10	1	0	3	1	5	0	1	0	0
BMW IX1	1	1	0	1	0	0	0	0	0	0
HYUNDAI KONA	32	2	0	0	3	2	0	2	0	0
KIA NIRO	81	4	0	11	8	6	1	7	0	0
KIA SOUL	5	1	0	1	2	1	0	1	0	0
NISSAN LEAF	23	2	0	0	1	1	0	1	0	0
PEUGEOT E 208	6	0	1	0	0	0	0	0	0	0
POLESTAR 2	18	1	0	0	2	3	0	3	0	0
RENAULT ZOE	53	14	0	19	10	2	0	2	0	9
SEAT MII ELECTRIC	2	0	0	1	0	0	0	0	0	0
SKODA ENYAQ	1	1	0	1	1	0	0	0	0	0
VOLKSWAGEN ID3	11	2	0	2	0	0	1	0	0	1
VOLKSWAGEN ID4	10	2	0	3	1	1	0	1	0	0
VOLKSWAGEN ID5	1	1	0	1	0	0	0	0	0	0
VOLKSWAGEN E GOLF	21	2	0	3	3	3	0	3	0	0
VOLVO C40	2	0	0	0	1	1	0	1	0	0
VOLVO XC40	11	2	0	0	1	4	0	4	0	0
OTHER MODELS	45	0	0	0	0	0	0	0	0	0

Data availability

The data cannot be shared currently. But part of the data will be available on request.

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