Energy & Buildings 241 (2021) 110923

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enb

Analysis of residential EV energy flexibility potential based on real-world charging reports and smart meter data

Å.L. Sørensen [a,b,*], K.B. Lindberg [a], I. Sartori [a], I. Andresen [b]

[a] SINTEF, Department of Architectural Engineering, P.O. Box 124 Blindern, 0314 Oslo, Norway
[b] Norwegian University of Science and Technology (NTNU), Department of Architecture and Technology, 7491 Trondheim, Norway

ARTICLE INFO

Article history:
Received 31 August 2020
Revised 1 March 2021
Accepted 14 March 2021
Available online 19 March 2021

Keywords:
Electric vehicle (EV) charging
Residential electricity demand
Load profiles
Energy flexibility
Bottom-up methodology

ABSTRACT

The increase in the number of electric vehicles leads to an increased demand for residential charging. While EV electric loads can have a negative impact on the power grid, they also represent a large potential for energy flexibility. This study proposes a methodology to describe charging habits, electricity load profiles, and flexibility potentials of EV charging in apartment buildings. The input data used for the method are generally available for buildings with multiple EV charge points: EV charging reports with individual charging sessions and aggregated smart meter data. The case study is a large housing cooperative in Norway, with a combination of private and shared charge points for the residents. The study compares two charging power assumptions of 3.6 kW and 7.2 kW. The flexibility potential increases with higher charging power. The study reveals a significant potential for residential EV charging flexibility when private parking spaces have EV charge points.

1. Introduction

1.1. Background

Electric mobility is growing rapidly, with China being the leading electric vehicle (EV) market, followed by Europe and the United States [1]. In terms of EV shares, Norway was the global leader in 2019, with 13% EVs of the total stock and 56% market share [1]. The growth in the number of EVs has led to an increased demand for residential charge points (CPs). Access to CPs has therefore become a topic of discussion in many Norwegian apartment buildings. In a survey from 2019, 94% of the EV owners living in single houses state that they charge at home weekly or more frequently, while 67% of the residents in apartment buildings state the same [2]. The Norwegian government has proposed to give apartment owners in housing cooperatives a statutory right to charge at home, under certain conditions [3]. However, local power grid capacity can be a limiting factor for new charging infrastructure. Facilitating for charging in housing cooperatives has become a grid capacity challenge, but also an opportunity for charge point operators (CPOs) with electricity load sharing possibilities [4].

EV electric loads represent a large potential for energy flexibility [5,6] and EVs are frequently considered in demand side management (DSM) systems [7]. With DSM, it is possible to affect the end-use of energy in a number of ways, by reducing (peak shaving), increasing (valley filling) or rescheduling (load shifting) the energy demand [8]. Knezovic [9] defines EV flexibility services as a power adjustment maintained from a particular moment for a certain duration at a specific location, characterised by the direction, the power capacity, the starting time, and the duration of the charging. If the EV is not vehicle to grid (V2G) capable, the flexibility direction is always the same. For residential DSM, it is essential that the comfort of the users is maintained [10]. Load shifting of EV-charging should therefore preferably not reduce the access to the cars, when needed by the residents.

EV charging infrastructure for residents in apartment blocks is often situated at common parking facilities. Typically, the residents share the general responsibility for the infrastructure. Even if the operating costs are eventually paid for by the residents using the CPs, the energy use is part of the common energy use in the housing cooperative, unlike energy use in apartments which usually are metered and paid for individually. EV charging in housing cooperatives is therefore more easily available for energy flexibility since it can be controlled by a single operator, compared to the energy loads in apartments.

Current knowledge of the characteristics of residential EV load profiles is limited [11,12]. More knowledge on charging habits, energy charged, and charging power, will make buildings owners more capable of utilizing the flexibility potential of EV charging, e.g. to reduce power peaks. This knowledge is also useful for distribution system operators (DSOs) and transmission system operators (TSOs), when evaluating the need for and alternatives to

* Corresponding author at: SINTEF, Department of Architectural Engineering, P.O. Box 124 Blindern, 0314 Oslo, Norway.

E-mail address: ase.sorensen@sintef.no (Å.L. Sørensen).

https://doi.org/10.1016/j.enbuild.2021.110923
0378-7788/

Nomenclature

AMS	Advanced Metering System, Smart meters
BEV	Battery Electric Vehicle
CCF	Cross-Correlation Function
CP	Charge point
CPO	Charge point operator
DSM	Demand side management
DSO	Distribution System Operator
EV	Electric Vehicle
IT230V	230 Volt IT system (distribution grid)
PHEV	Plug-in Hybrid Electric Vehicle
SoC	State of Charge of the battery
V2G	Vehicle to Grid
#	Number of

future grid capacity expansions [13]. This paper proposes a methodology for analysis of residential EV energy flexibility potential that can use input data that are generally available for building owners with multiple EV CPs. CPOs are often involved when there is a pool of public or private CPs from one or more manufacturers. EV charging reports are typically made available for the charging infrastructure owner, for the purposes of invoicing and data management. The reports include information such as plug-in time, plug-out time, and energy charged, all linked to a user and a CP. It is less common that the Norwegian charging reports contain information on actual charging time or charging power. Smart meter data is another available data source. In Norway, all DSOs have been obliged to install advanced metering system (AMS) for all customers by the Norwegian regulator (NVE) by 1.1.2019 [14]. This makes hourly electricity meter readings easily available.

The main research question of this work is: How can EV charging reports and smart meter data describe charging habits, electricity load profiles, and flexibility potential of EV charging in apartment buildings? The paper is structured as follows. Section 1.2 provides a brief literature review of real-world EV charging data analyses, while Section 1.3 describes the contribution of this work. Section 2 introduces the case study, and describes EV charging power and charge characteristics of EV batteries. The methodology is described in Section 3, while Section 4 presents the results and a discussion of the findings with respect to EV charging habits, EV energy loads and EV charging flexibility. Finally, the conclusion of the paper is drawn in Section 5.

1.2. Literature review

A number of studies have analysed real world EV charging data based on EV charging reports from CPOs. Other data sources also form the basis for charging data analyses, including mobility datasets (e.g. [15–18]) or Global Positioning System (GPS) data from the EVs (e.g. [19,20]). In addition, some articles have based their work on charging assumptions or expected values for EV charging habits (e.g. [21]), or EV information available from questionnaires (e.g. [22,23]).

The studies [24–26,12] analyse EV charging and flexibility based on EV charging reports from public charging stations in the Netherlands. The research in these studies are based on charging session-information with plug-in and plug-out times, charging times, connection times, idle times with no charging, as well as energy or power information. Sadeghianpourhamami et al. [24] have clustered the arrival and departure time combinations for nearly 400,000 charging sessions, with the three clusters "Park to charge", "Charge near home" and "Charge near work". The cluster "Charge near home" has arrivals in the afternoon/evening with departures mostly in the morning the next day. This cluster was therefore identified as the best candidate for moving charging demand to night-time. Gerritsma et al. [25] have categorized anonymous EV IDs for 8223 charging sessions according to local or visiting EVs, where the local users charge more frequently and with longer connection times. Analysing flexibility, the researchers found that 59% of the aggregated EV demand could be delayed for more than 8 h. Furthermore, they found that local EVs charge longer and have a larger potential for flexibility, compared to visiting EVs, especially when it comes to moving the evening peak to the night. Flammini et al. [26] analysed 400,000 charging sessions in publicly accessible charging stations. 1213 of the 1744 charging stations were found to be localized next to roads categorized as residential, while the remaining charging stations were located by four other road classifications with higher vehicle capacity. The study found that connection and non-charging idle times were higher for EV charging in residential areas, where the average connection time was about 7 h, compared to the other road classifications. They also found that chargers in residential areas had a higher utilisation rate, which suggests that drivers prefer charging close to their home. Both [24,25] point out that there are few examples from literature where EV flexibility has been analysed or quantified, e.g. by finding the difference between connection times and charging times.

Research groups in other countries have also analysed EV charging reports. Xydas et al. [27] (UK) describe an EV study, providing a cluster analysis of 22,000 charging sessions from 255 public charging stations. The study investigates the charging impact on the distribution network. They conclude that DSM of EV charging can be designed for charging habits in specific areas, e.g. dependent on if the EV charging load is high during peak times or more randomly distributed. The research by Quirós-Tortós et al. [28] is not based on typical charging reports, since the available data are from a research trial with onboard monitoring in EVs, but still with similar type of data available, such as plug-in and plug-out times, as well as initial and final state of charge (SoC). The research presents monitoring of 221 EVs and reports data from 68,000 residential charging sessions, together with other residential electricity use. Neaimeh et al. [29] combine charging data from onboard monitoring in 44 EVs with data from nearly 9000 residential smart meters, to study the impact of EVs on electricity distribution networks. Khoo et al. [30] describe charging reports from a trial in Australia, involving 121 households and 57 corporate participants. The study found that each charging session in the households lasted in average 2.5 h and consumed 6 kWh. The researchers in [31] present data from 2000 non-residential EVs in California, US, with plug-in/plug-out times corresponding with typical working hours. The study compares the benefits of smart charging from an EV charging service provider's perspective to the benefits from a DSO's perspective.

Several researchers have analysed EV charging based on energy measurements. Studies such as [32] (US), [33] (US) and [34] (Norway/US) quantify EV charging and flexibility using a top-down approach, analysing electricity metering data for many households with or without EVs. However, few bottom-up analyses are identified, where hourly meter values are combined with other data sources available for the building owner. Apartment buildings typically have several AMS-meters measuring electricity use in common areas [6], where it is not unusual that a meter measure aggregated EV charging mainly.

1.3. Contribution of this work

Even though several articles recognize the flexibility potential of residential EV charging, few studies analyse real data from residential EV charging in apartment buildings. This paper aims to fill this gap, by proposing a methodology that combines information which is commonly available for building owners: EV charging reports from the CPO and hourly smart meter data from the DSO. These data sources are generally available for apartment buildings in Norway, which makes wide scale use of this methodology possible. Specifically, the methodology introduced in this work provide:

- Flexibility potential of residential charging:
  The bottom-up analysis of EV charging and flexibility uses commonly available data sources. Daily profiles for charging load and flexibility are provided per user, which is useful e.g. when estimating future charging loads with an increasing number of EVs or charging loads in other locations.
- Distinctions of ownership of chargers:
  EV charging is analysed for users with their own CPs at individual parking spaces or shared CPs available for all the residents. How charging habits depend on CP location and ownership has not been studied in the literature identified in the review.
- Correlation between plug-in/plug-out times and local hourly traffic data:
  A link between plug-in/plug-out times and local hourly traffic data is analysed, and thus provides new possibilities for planning and simulations of residential charging. The review of the literature has not identified other bottom-up studies focussing on this link.

2. Introduction to case study, EV charging power and charge characteristics of EV batteries

2.1. Introduction to case study: Risvollan housing cooperative

Norway has a high share of EVs, compared to the EV share in other countries [1]. EV charging experiences and data from Norway can therefore be useful also for other countries in Europe and worldwide. This is especially relevant for apartment buildings, where there is a lack of data on aggregated residential charging in the literature, even though the flexibility potential is recognized. Besides serving as s a case study for the developing a new methodology, the numeric findings from the case study may also be useful in a wider context. The case study chosen represents apartment buildings with newly installed EV charging infrastructure, and an increasing number of EV users. With an increasing share of EVs worldwide, lessons learned from this case study may be relevant for many other building estates in a similar situation.

The case study is located in Trondheim, Norway, in a suburb that is located 6 km from the city centre. Risvollan housing cooperative has about 2400 residents living in 1113 apartments, where 95% of the apartments are located in 121 similar apartment blocks (Fig. 1). Space heating and domestic hot water (DHW) are provided by district heating. Table 1 summarizes building data and information about energy use in Risvollan housing cooperative, based on an energy analyses of 95% of the apartments in 2018 [6,35].

During the first 11 months of 2018, it was possible to charge approximately 55 EVs in the garages of the housing cooperative. A new infrastructure for EV charging was installed in December 2018, making it possible to activate up to 764 CPs in the garages. The charging infrastructure balances the EV loads in each garage, to make sure the aggregated charging power is below the power limit. The CPO registers all charging sessions including plug-in times, plug-out times, and charged energy. From December 2018 to January 2020, 6878 charging sessions were registered by 97 different user IDs; 82 of these IDs appeared to be still active at the end of the period. The EVs were parked in 24 different parking locations, each with an AMS-meter measuring the aggregated EV-

Fig. 1. Example of apartment blocks in case study.

Table 1
Key information on the case study.

# Apartments	1113
in 121 building blocks	1058
in 1 tall building block	55
# Residents in 121 building blocks	2321
Total heated apartment area (m^2)	96,254
Specific electricity use (kWh/m^2)	56.7
Share, el use in common areas/apartments	13%/87%
Specific heat delivery (kWh/m^2)	139

charging at that location. Table 2 summarises charging information available from Risvollan. Fig. 2 shows hourly energy use aggregated in 22 of the 24 garages. The number of EV users is increasing from zero to 82 during the period, with in average 53 users. The number of EV users shown is EV users registered per day, with new EV users added and inactive users deactivated (see Section 3.1). For January 2020, the figure shows the total number of EV users active during the last month, which is 82.

The price structure for charging in the case study is not expected to influence charging habits or timing. The users pay for the electricity charged, using the same spot-market-based electricity tariffs as for the electricity use in the housing cooperative (this varies typically between 1 and 1.5 NOK/kWh). The energy cost for charging at shared and private CPs is the same, but residents using shared CPs are encouraged to park for <3 h. Typically, home charging has a lower price, compared to paid non-residential charging. However, workplace charging can be free of charge, but is often limited.

2.2. EV charging power and energy

For residential charging of EVs, both the onboard charger in the EV and the available AC power can be limiting factors for the EV charging power. Fig. 3 shows nominal onboard charger capacity (kW AC) for battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) on the market, based on an overview of EVs from [36,37]. The plot includes new models of BEVs and PHEVs as well as earlier models for the most typical BEVs on the Norwegian market. There are five typical levels for the onboard charger capacities: 3 to 3.7 kW, 6.6 to 7.4 kW, 11 kW, 16.5 kW and 22 kW. Charging capacity for most BEVs is between 3.3 and 11 kW. For PHEV, the onboard charger capacity is typically between 3.3 and 3.7 kW.

In Norway, residential customers are normally connected to a type 230 Volt IT system. Power use during residential EV charging is typically 2.3 kW when using a household power plug (10 A) and 3.6 kW or 7.4 kW when using a Type 2 connector (16 or 32 A). For some charging systems, it is possible to activate 3-phase charging on IT230V, increasing the charging power. In the case study, 7.4 kW is available for all customers and 11 kW is available if activating 3-phase charging.

Fig. 3 also shows typical gross battery capacities for BEVs and PHEVs. For BEVs on the market from 2018 to 2020, most batteries

Table 2
Data sources for EV charging information.

AMS-meters	Hourly electricity measurements in 22 locations (kWh/h)								
EV charging report from CPO	Per address/charger ID/user ID: Plug-in time, Plug-out time, Charged energy (kWh)								
Data collection period	From December 21, 2018 to January 31, 2020								
# addresses/garages	24								
Ownership of the CPs	Private			Shared			Total		
	Dec18	Jan20	average	Dec18	Jan20	average	Dec18	Jan20	average
# CPs	0	58	25	0	12	8	0	70	33
# User IDs	0	58	35	0	24	18	0	82	53
# Charging sessions	5466			1412			6878		

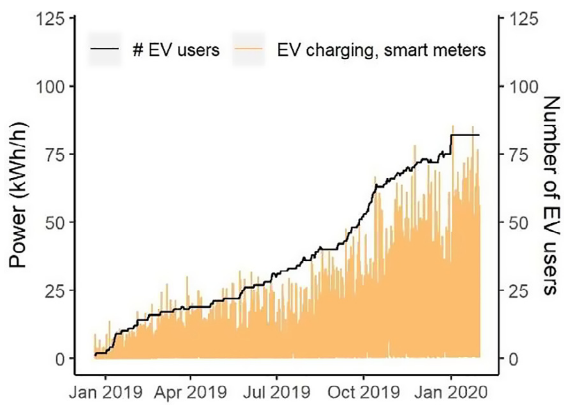

Fig. 2. Hourly energy use in 22 of the 24 garages (aggregated) and the increasing number of EV users during the period.

have nominal capacities between 40 and 100 kWh. Due to charging efficiency, energy use for charging is higher than the charged energy. The efficiency vary, and [38,39] have found energy losses between 12% and 40%.

2.3. Charge characteristics of EV batteries

Later in this study, it is assumed that the energy charged each hour is constant, independent of type of EV, battery SoC, etc. However, this is a simplification, and this section gives an introduction to charge characteristics of EV batteries.

Lithium-ion (Li-ion) batteries are the market leader for use in EVs, mainly because of their high specific energy cycle life and high efficiency [40]. The Li-ion battery pack in an EV consists of a large number of single battery cells, arranged in serial, parallel or hybrid forms [41]. Typical charging characteristics for a single battery cell is shown in Fig. A1 in the Appendix, described as constant current – constant voltage (CC-CV). The charging capacity is gradually increasing with a constant current, until the battery reaches the maximum charging voltage. The current then drops to maintain this charging voltage while preventing overcharging the cells [43]. A battery management system is needed to monitor, manage and protect the Li-ion battery charging [44]. Charging and discharging within the ideal operating range of the SoC, i.e. 20%-90%, is a topic within such management [42].

Fig. A2 in the Appendix shows charging characteristics of two example charging sessions by two EVs in the case study. The car types for the two EVs are marked in Fig. 3, as example EV mid-range and long-range. The nominal onboard charger capacity of the cars is 7.2 kW for the mid-range EV and 11 kW for the long-range EV. However, since 3-phase charging is not activated for the cars, the long-range EV is limited to 1-phase charging power of 7.4 kW. The nominal battery capacity is 36 kWh for the mid-range EV and 75 kWh for the long-range EV. The charging sessions last for about three hours, where both of the EVs charge around 20 kWh. The current for both cars is reduced by about 8% during the charging sessions, while the voltage is constant. The reduction in current is less than presented as typical charging characteristics in Fig. A1. However, the current reduction is EV and SoC dependent. For the long-range EV, the constant current could be explained by the owner's statement that the charging is normally discontinued automatically at 80% battery capacity. For the middle-range EV, [22] found that for this type of EVs, the charging ends instantly when the battery has reached its full charged level.

3. Methodology

The suggested methodology in this article is developed to describe charging habits, electricity load profiles and flexibility potential of EV charging in apartment buildings. The main data sources are: EV charging reports with 6878 individual charging sessions, hourly AMS data from 22 garages, and local hourly traffic data. The data was collected from 21 Dec 2018 to 31 Jan 2020.

A flow chart of the methodology is shown in Fig. 4. First, EV charging reports are used for analysing charging habits. Secondly, EV charging and flexibility potential are estimated. The results are validated using hourly AMS data. The data are analysed using the statistical computing environment R [45].

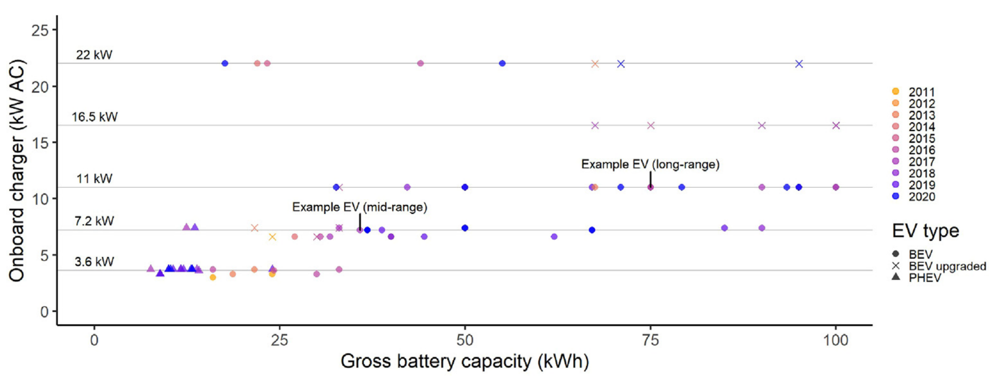

Fig. 3. Nominal onboard charger capacity and gross battery capacity for BEVs and PHEVs on the market.

3.1. Data preparation

The EV charging reports include plug-in times, plug-out times, and charged energy per charging session. Each charging session is connected to a user ID, a charger ID, and an address. The charger IDs are either private or shared, since the CPs are either located on the residents' private parking spaces or on shared parking areas available for all residents. The original charging reports have 7245 charging sessions. The main steps of initial data cleaning include removing unrealistic charging sessions (1 charger with 29 charging sessions removed) and charging sessions with no energy charged (338 charging sessions removed). If the plug-out time is too early when compared to energy charged and maximum 11 kW charging power available, the plug-out time is removed (set to NA), since this indicates that the value is incorrect (relevant for 34 charging sessions). Further, there is quality assurance to assure correct data time zones/daylight saving time (DST), before calendar data is added, such as weekdays and months.

Hourly electricity data from 22 of the 24 AMS-meters in the garages are provided by the DSO. The two missing AMS-meters are connected to four EV users only, with in total 4500 kWh charging energy from 353 charging sessions (5% of all charging sessions). Each of the AMS-meters measures the aggregated EV-charging on that location. Hourly energy estimates provided by the DSO are removed from the data (4% of the hourly values), since inaccurate hourly values may influence the results.

Hourly traffic data from five nearby locations are provided by [46]. Hourly counts are available for vehicles with different sizes. The hourly count of small cars (<5.6 m) is used in the analysis, as an average of the traffic measured by the five nearest traffic stations.

3.2. Analysing EV charging habits

EV charging habits are analysed showing the daily distribution of EV plug-in and plug-out times during weekdays and weekends, and histograms for connection times (related to plug-in time) and energy charged (related to plug-in time and connection time). EV charging habits are analysed separately for private and shared CPs.

The daily distribution of plug-in and plug-out times is compared to hourly traffic data from nearby locations. The correlation between plug-in/plug-out times and local hourly traffic data is explored by using the cross-correlation function (CCF), which is a function used to evaluate the correlation between time series. CCF is a "wrapper" function calling the autocorrelation function (ACF), as described by [47], page 390–392]. To find the correlation, the function ccf() is used in R [48]. CCF examines the cross-correlation between the number of plug-ins or plug-outs each hour and the hourly number of cars, where the maximum value for correlation is 1. Before calculating the CCF, the dataset is split into charging sessions using private and public CPs, respectively.

3.3. Estimating EV energy load and flexibility potential

The energy loads and flexibility potential of EV charging are estimated as follows. The differences between the plug-in and plug-out times of the charging sessions provides the duration of the EV connection time (Eq. (1)). The actual charging times and charging power are not known. In the method, two alternative charging powers ($P_{charging}$) are assumed: 3.6 or 7.2 kWh/h, representing typical levels for the onboard charger capacities as described in Section 2.2. The assumed charging power is the average charging power during an hour. When estimating hourly EV energy loads for a specific charging session, the synthetic charging time is first calculated, by dividing the actual charged energy ($E_{charged}$ from the EV charging report), on the assumed charging power (Eq. (2)). The hourly charging loads equal the assumed charging power multiplied by time (Eq. (3)). For the first hour, the maximum charging time is calculated as the number of minutes after the plug-in time. For full hours after the initial hour, the hourly charging load equals the assumed charging power. For the last hour, the charging load equals the remaining energy difference, so total energy charged during the charging session equals the actual charged energy, known from the EV charging report. The method provides a synthetic charging time and energy load, given immediate charging after plug-in. Average daily charging load profiles are shown for different weekdays and holiday periods.

$$\text{EV connection time: } t_{connection} = t_{plug-out} - t_{plug-in} \tag{1}$$

$$\text{EV charging time: } t_{charging} = E_{charged}/P_{charging} \tag{2}$$

$$\text{EV load hour } i\text{: } E_{load(i)} = t_{(i)} \cdot P_{\ charging} \text{ where } \sum \left(E_{load(i)}\right) = E_{charged} \tag{3}$$

$$\text{EV idle time: } t_{idle} = t_{connection} - t_{\ charging} \tag{4}$$

$$\text{EV idle capacity hour } i\text{: } E_{idle(i)} = t_{idle(i)} \cdot P_{charging} \tag{5}$$

The difference (non-charging *idle time*) between the EV connection time and the synthetic charging time reflects the flexibility potential for the charging session (Eq. (4)). The *idle capacity* is the energy which could potentially have been charged during the non-charging idle times. The idle capacity is analysed for the assumed charging power of 3.6 and 7.2 kWh/h. To calculate the hourly idle capacities for hours with non-charging idle time, the hourly idle times are multiplied by the assumed charging power (Eq. (5)).

Initially, the database includes synthetic estimates for all charging sessions separately. Only hours with charging loads or idle capacities are included. An hourly aggregated database is created by grouping the data per hour. Hours with no charging or idle capacities are added to the aggregated database, to assure a full hourly timeseries for the period, from mid-December 2018 to end-January 2020.

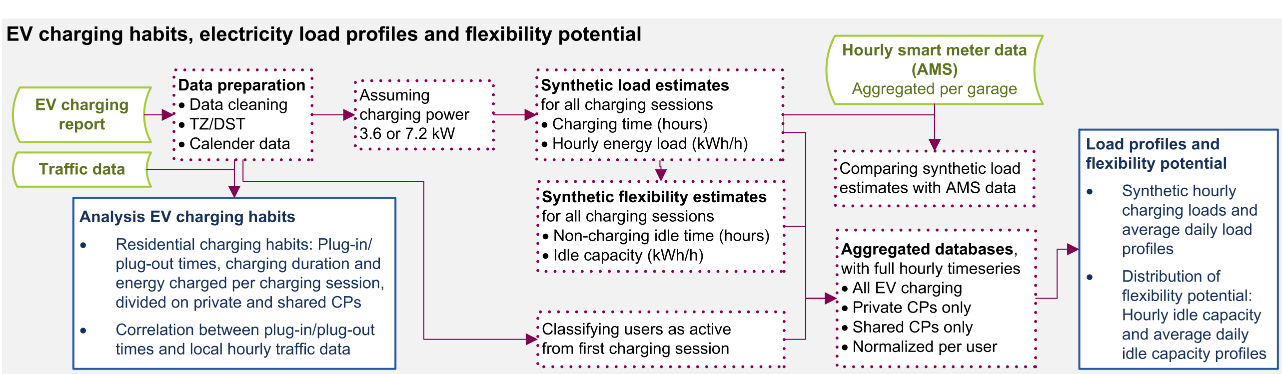

Fig. 4. Flow chart outlining the methodology. Green boxes show data sources, red boxes show processes, and blue boxes show results. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Since the number of EV users is increasing during the measurement period, energy and power results are also presented normalized per user. The users are classified as active from the date of their first charging session (user has value NA before and 1 after first connection). In addition, some users become inactive, if they for example move or if a user with shared CP becomes a user with private CP. Users with NA values towards the end of the measurement period are classified as inactive and not included in the number of EV users. The change of classification takes place after their last charging session, from their first inactive date. However, during the last month (January 2020), only users not charging at all during the month were classified as inactive, to avoid wrong classification of users that are travelling, etc.

The classification of active users makes it possible to divide the hourly aggregated values for charging loads and idle capacities on the current number of users, to get e.g. typical average load profiles per user. When analysing selections of the dataset, such as users with private/shared CPs, hours with no charging are added to the data to assure full hourly time series. Before their first charging session (and after their last charging session, if becoming inactive), energy values are set to NA during hours with no charging, while energy values are zero after the first charging session. This is done to assure correct average values.

3.4. Validation of the methodology

The synthetic hourly EV energy loads are compared to AMS data per garage. AMS data are available from 22 of the 24 garages (95% of the charging sessions). Some differences between the total AMS data and the total charging energy from the charging reports can be expected, since there may also be other electricity use metered in the garages. For 20 of the garages in the case study, the total energy charged is <10% different from the AMS data in the specific garage, while the AMS data is 20% higher in one garage. For the last garage, the AMS data is 50% higher, but this garage includes the user which was removed in the initial data cleaning. It can therefore be concluded that in the case study garages, there is little electricity use measured by the AMS-meters other than EV charging.

The charging infrastructure in the case study has the possibility to balance the EV loads in each garage, when the aggregated EV load is high. However, a similar load balance is not included in the synthetic loads. Some differences may therefore be expected in the hourly aggregated loads per garage, especially when the loads are high.

Fig. 5 shows an example from a garage (Bl2) for four days, where synthetic hourly EV energy loads are compared to AMS data. For the garage shown, the total AMS data is 28.2 MWh during the measurement period, which is only 4% higher than the total charging energy reported for the same garage. The figure highlights examples of individual charging sessions, marked with a square. When there is one charging session only, the highlighted charging sessions in the figure show an agreement between the hourly measured charging power and the hourly estimates, with a charging power close to 7.2 kW (November 2nd) and 3.6 kW (November 5th). When there are several charging sessions aggregated, the measured charging power is often between the two estimates.

4. Results and discussion

4.1. EV charging habits

This section aims to answer how EV charging reports can describe EV charging habits for residents. Figs. 6 and 7 show how the plug-in and plug-out times are distributed during weekdays and weekends, for private and shared CPs, as well as the daily distribution of cars in near-by traffic. The plug-in time for the charging (Fig. 6) is mainly in the afternoons during workdays, both for the private and the shared CPs. There is a peak around 16:00, with around 15% of the plug-ins during the day, which corresponds to when the workdays typically end in Norway. An afternoon peak is also present in the near-by traffic density. During the weekends, the plug-ins are more evenly distributed during the day, corresponding to the nearby traffic. For plug-out times (Fig. 7), private CPs have a peak in the morning, between 07:00 and 08:00, corresponding to the start of a typical workday. This peak is also present in the traffic density. For shared CPs, the morning peak is less substantial, indicating that the users move their car sooner after finishing the charging. The residents using the shared CPs are encouraged to charge for <3 h.

The case study results indicate that the hourly plug-in/plug-out times correspond well to local traffic data. Fig. 8 describes the CCF values between the number of plug-in (left) or plug-out (right) times each hour and the hourly number of cars. Each lag is equivalent to 1 h. In the figure, a seasonality of h = 24 is observed, with a strong dependence between the plug-in/plug-out times and the local traffic. The CCF correlation coefficients at lag 0 and 1 are 0.296 and 0.363 respectively for plug-in/local traffic and 0.345 and 0.278 for plug-out/local traffic. Such correlations provide possibilities for developing new models to estimate EV charging loads at different locations, where local hourly traffic data can be used as input.

The histograms in Fig. 9 show connection times for charging sessions. The histograms confirm that residents using shared CPs often have shorter connection times than residents with private CPs. For private CPs, the average connection time is 12.8 h, while 90% are connected for <22.6 h. For shared CPs, the equivalent connection times are 6.5 h on average, and 14.3 h for 90% of the charging sessions. The histograms show a twin peak in the connection times, which can be explained by the plug-in time for the charging sessions. The first peak occurs for charging sessions with <5 h of connection time, where typically the plug-in time is in the daytime, afternoon, or early evening. The second peak is for charging sessions with connection time between 8 and 15 h (longer for private CPs), with plug-in time typically in the evening and connection through the night. The average connection time differs according to the weekday when the charging started, where especially Sundays stand out for residents with private CPs. When plugged in during weekdays, 73% of the charging sessions are longer than three hours. The corresponding share for plug-in during Sundays, is 84%.

Figs. 10 and 11 show histograms for energy charged per charging session, divided according to private and shared CPs. The histograms are the same, but the colours in Fig. 10 are related to plug-in time, while the colours in Fig. 11 are related to connection time. The average energy charged per session is 11.2 kWh for users using private CPs and 14.7 kWh for shared CPs. For 90% of the charging sessions, energy charged is below 22.0 kWh per session for the private CPs and 39.5 kWh per session for the shared CPs. The explanation for why users with shared CPs charge more energy, may be that these users wait to charge until the battery has a lower SoC compared to users with private CPs at their own parking space, and the shared CP users therefore charge less frequently. This is confirmed by the average number of daily charging sessions per user: The users with private CPs have an average of 4.4 charging sessions per week, which is a factor of about 3.5 higher than the users with shared CPs, where the average is 1.2 charging sessions per week. Fig. 11 shows that there is no direct relationship between energy charged and connection time. Private CPs often have a longer connection time than shared CPs, for the same amount of energy charged. The outcome of this is a longer non-charging idle time for private charging sessions, which results in a higher potential for flexibility.

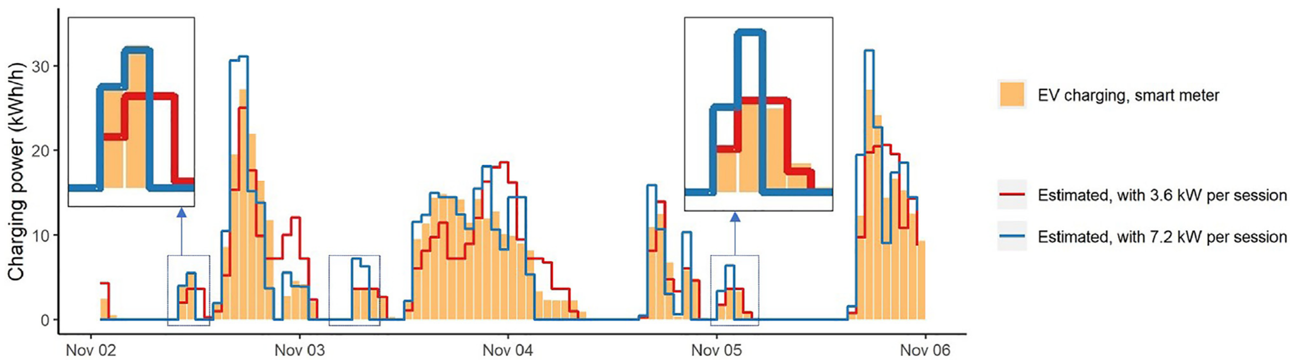

Fig. 5. Validating the methodology for four days in garage Bl2. Synthetic hourly EV energy loads are compared to smart meter data. Three individual charging sessions are highlighted with grey squares.

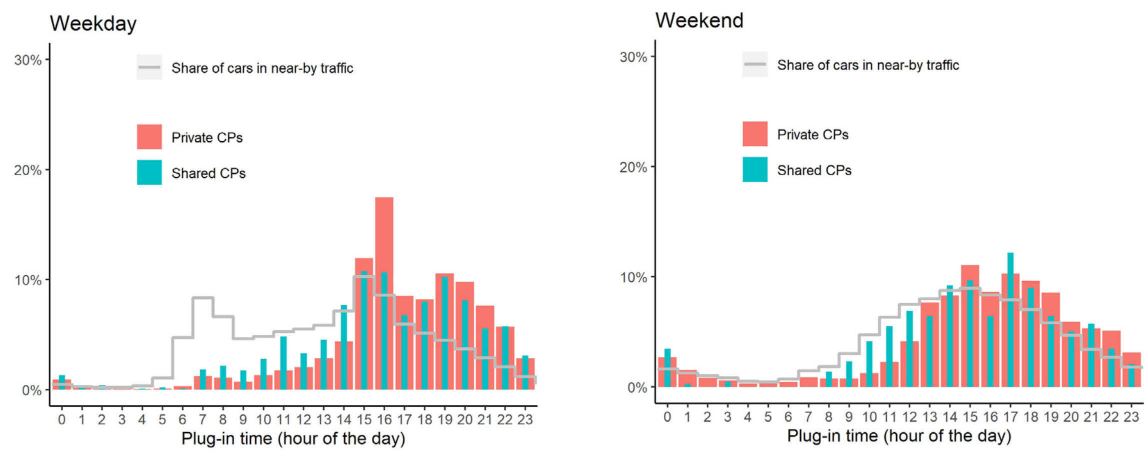

Fig. 6. Plug-in times: Average daily distribution of EV plug-in times during weekdays (left) and weekends (right), for private and shared CPs, as well as average daily distribution of cars in near-by traffic.

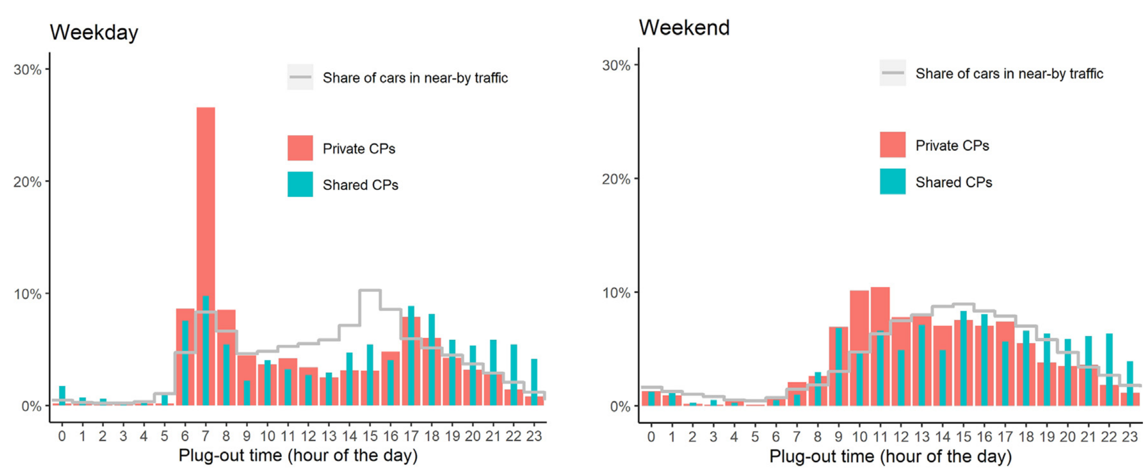

Fig. 7. Plug-out times: Average daily distribution of EV plug-out times during weekdays (left) and weekends (right), for private and shared CPs, as well as average daily distribution of near-by traffic.

4.2. EV energy load

This section aims to answer how information in EV charging reports can be translated into synthetic hourly EV energy loads. To answer this question, information about plug-in times and energy charged from the charging reports is combined with charging power assumptions.

The monthly energy charged per user is estimated from January 2019 to January 2020, as shown in Fig. A3 in the Appendix. For the monthly distribution, a charging power of 3.6 kW is assumed. The charging power assumption is especially relevant for charging sessions with a plug-in time late in a month and a plug-out time in the following month. Since monthly energy charged vary between the users, the results are shown in boxplots. In the boxplots, 50% of the monthly values are in the boxes within the first (Q1) and third (Q3) quartile, with the median monthly value in the middle. The vertical lines represent the least and greatest monthly value excluding outliers. Black dots show outliers, which are defined as values

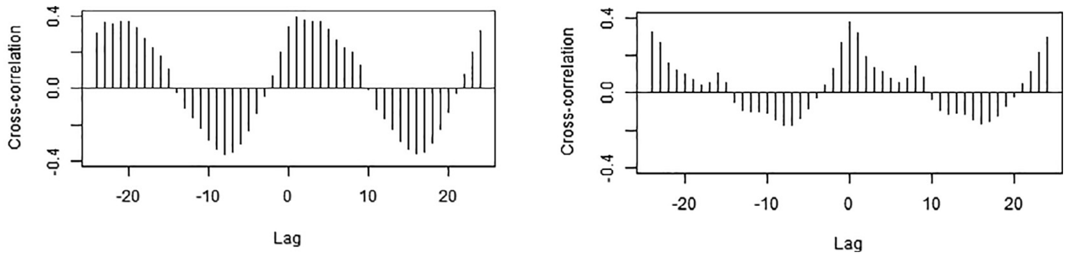

Fig. 8. CCF between the number of plug-ins and number of cars in nearby traffic (left) or plug-outs and number of cars (right) each hour.

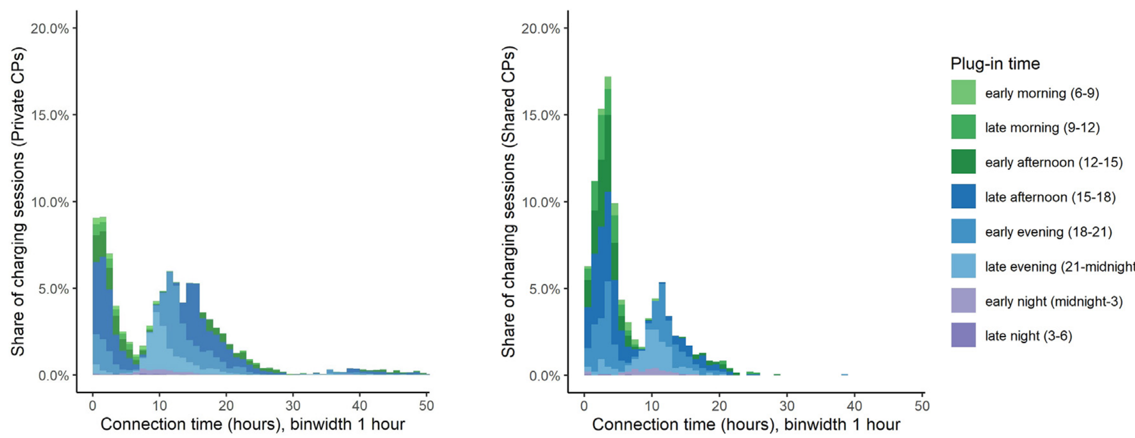

Fig. 9. Histogram for connection time related to plug-in time, for private (left) and shared (right) CPs. Binwidth is 1 h, showing the first 48 h only.

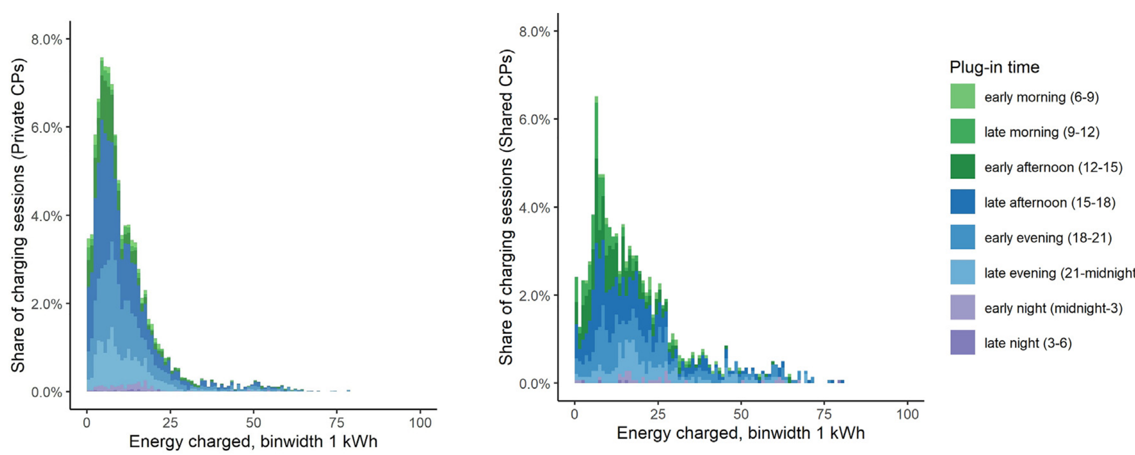

Fig. 10. Histogram for energy charged related to plug-in time, for private (left) and shared (right) CPs. Binwidth is 1 kWh.

extending 1.5 times the interquartile range (IQR = Q3-Q1) out from the box. The red dots represent the average values. The data are divided into users with private or shared CPs. For users with private CPs, the monthly values during the first two months are lower than the average. The reason for this may be that a large share of the users is registered in the middle of the month, resulting in less monthly days available for charging. There are also values that are lower than average in July, which is the main holiday month in Norway.

For users with private CPs, the average monthly energy use during the period is 179 kWh per user, or about 2150 kWh per year. For users with shared CPs, the average monthly energy use is 125 kWh per user, or about 1500 kWh per year. Assuming an average driving efficiency of 5 km/kWh, this corresponds to, on average, 10,700 km for users with private CPs or, on average, 7500 km for users with shared CPs. As a comparison, the average yearly driving distance for EVs in Norway was 12,631 km in 2019 [49]. However, as stated in the introduction, it is expected that the EVs are not being charged at their home address only. The estimated annual driving distances confirm an expectation that users with shared CPs charge less at home, compared to users with private CPs at their parking space.

The synthetic hourly aggregated peak power values each month are shown in Fig. 12, assuming a charging power of 3.6 kW and 7.2 kW, respectively. The figure shows the hourly aggregated max peak loads per month, as well as the 99th and 90th percentiles of the hourly load values. The total aggregated power is increasing during the period (left figure), since also the number of users is increasing. However, the peak power per user is reduced with increasing number of users (right figure), due to a lower coincidence factor. The coincidence factor is defined as the ratio between maximum load for the aggregated data studied and the sum of each users' maximum load [50]. For example, for the 20 users in March 2020, the coincidence factor was 0.43, decreasing to 0.25 for the 82 users in January 2020, assuming charging power 3.6 kW.

For the aggregated load (left figure), the monthly max. peak for the charging power of 7.2 kW is a factor 1.1 to 1.5 higher than the

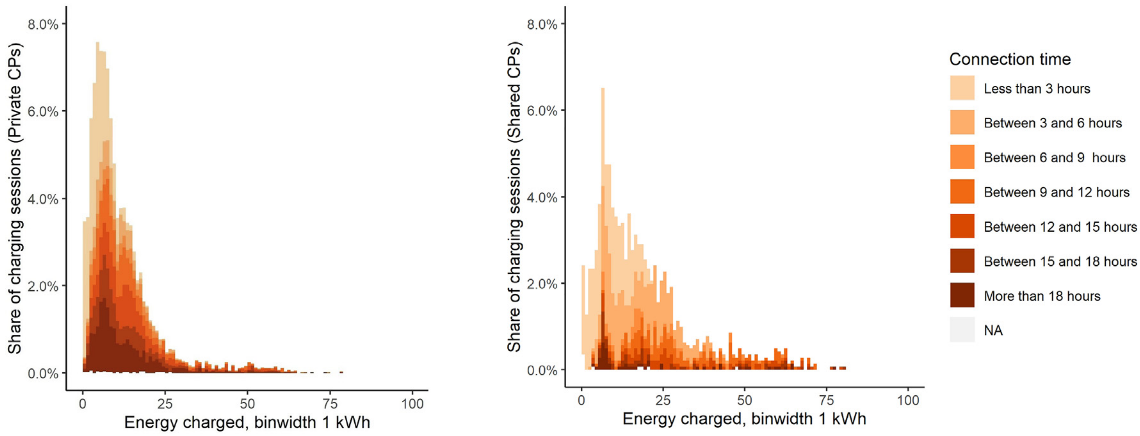

Fig. 11. Histogram for energy charged related to connection time, for private (left) and shared (right) CPs. Binwidth is 1 kWh.

max. peak for the charging power of 3.6 kW. The max. power peaks are not so frequent, shown by the difference between the peak loads, 99th and 90th percentiles. For the charging power of 7.2 kW, the max. peak power each month is a factor 1.6 to 3.3 higher than the 90th percentile. Equivalent, for the 3.6 kW charging power, the max. peak power each month is a factor 1.6 to 2.2 higher than the 90th percentile. When utilizing the potential EV charging flexibility, the operator often wishes to reduce the highest aggregated EV power peaks, getting values closer to the 99th percentile, the 90th percentile, or even lower, towards the average power.

The average load profile for weekdays shows an increased energy use in the afternoons and evenings, with the highest load occurring from about 16:00 to midnight. The weekend profile is quite similar, but without the afternoon peak. For the average values, the hourly load for the 7.2 kW charging power is up to a factor 1.3 higher than for 3.6 kW charging power. This happens during afternoons/evenings when many users have recently plugged in their EVs, with the largest difference occurring from 15:00 to 17:00 on weekdays, and from 13:00 to 20:00 on weekends. During the night/morning, from 23:00 to 12:00, the hourly load for the 3.6 kW charging power is higher than for the 7.2 kW charging power, since the cars with higher charging power finish charging earlier.

The average values shown in Fig. 13 do not illustrate how EV charging typically varies during the year. For example, holiday periods tend to deviate from the average values. Assuming a charging power of 3.6 kW, Fig. 14 shows the average daily charging load profiles for an average weekday, Saturday and Sunday. The average charging need during the week is 37.5 kWh per user. Most weekdays have similar charging needs, with Tuesdays somewhat lower (−7%) and Thursdays (+4%) and Fridays (+5%) somewhat higher than the weekly mean values. Saturdays have −13% lower and Sundays +8% higher values, compared to the weekly mean values. Fig. 14 also illustrates the daily load profiles during holiday periods. During July, the energy demand is lower than for the average profile (ref. Fig. A3), but otherwise quite similar to the average. For the holiday week in October, the charging need at Sunday evenings increase when residents come home from travelling. For Christmas, there is an increased charging need during the day before Christmas (Monday 23 December), while the residents charge earlier on Christmas Eve (Tuesday 24 December) than on an average Tuesday. The charging power is shown per number of users during the different periods: 57 users in average, 33 in July, 59 in October and 75 during Christmas 2019.

In addition to charging the battery, EVs can use energy to preheat the battery and cabin. This is not taken into account in the methodology, but it is not expected to significantly affect the daily charging load profiles in the case study, since most EVs are parked in garages.

4.3. EV charging flexibility

This section aims to answer how non-charging idle times can be translated into energy flexibility potential. From the charging reports, the EV connection times (the difference between plug-in and plug-out times) and charged energy are known per charging session. Two alternative EV charging times are calculated, assuming different levels of charging power (3.6 or 7.2 kW). The non-charging *idle time* between the EV connection time and the charging time reflects the flexibility potential for a charging session. Fig. 15 shows an example of a single charging session, with charging power 3.6 or 7.2 kW. Energy charged and connection time is the same in both figures (11.3 kWh and 13.5 h connection time), and has quite typical values as shown in Figs. 9 and 10. The flexibility potential in the figures, termed *idle capacity,* is the energy which could potentially have been charged during the non-charging idle times. However, since the actual energy charged dur-

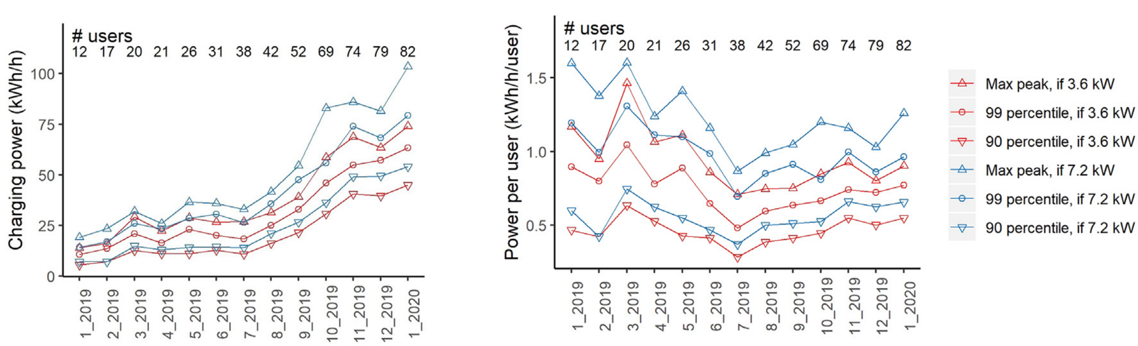

Fig. 12. Estimated hourly aggregated peak power (left) and power per user (right), with increasing number of users, assuming charging power 3.6 kW and 7.2 kW.

ing a charging session is the same, the idle capacity is higher with higher charging power. For the example session in Fig. 15, the idle capacity is a factor 2.3 higher when the charging power is 7.2 kW, than when it is 3.6 kW.

Fig. 16 shows an example of charging load and idle capacity for aggregated EV charging in a garage (Bl2) during a week, with assumed charging power 3.6 or 7.2 kW. During the week, there are 78 charging sessions in the garage, charged by 17 users. Energy charged is the same in both figures (around 930 kWh), while the idle capacity is 1200 kWh for the charging power of 3.6 kW and 3100 kWh for the charging power of 7.2 kW. Comparing the two charging levels during the week, the hourly aggregated charging peaks increase with a factor 1.2, going from 3.6 to 7.2 kW charging power, assuming immediate charging after plug-in. During the same week, the idle capacity for charging power 7.2 kW is a factor 2.6 higher than for charging power 3.6 kW. However, for idle capacity, the periods after the charging peaks are normally of most interest, since charging loads can be delayed in time. Also, idle capacity during other periods can be relevant, such as times with locally available RES. For the example week in Fig. 16, there is high idle capacity during night-time and a potential for moving afternoon- and evening charging loads to night-time, for both charging powers of 3.6 and 7.2 kW, respectively. If charging loads are moved to the daytime, for example to utilize photovoltaic (PV) solar energy, the idle capacity during the day is higher during the weekend than on weekdays. Comparing the two charging power levels in the selected week, the 7.2 charging power has a higher potential for daytime charging than does the 3.6 kW charging power.

Synthetic average daily charging load profiles and idle capacity profiles per user are shown in Fig. 17, for the aggregated EV charging during weekdays, assuming immediate charging after plug-in. The figures show the profiles with the 3.6 kW charging capacity (top) and the 7.2 kW charging capacity (bottom). The boxplot illustrates the distribution of hourly load values. As in Fig. 13, the average aggregated charging load is similar for the two charging capacities. The average daily idle capacity differs, with higher values when the charging capacity is 7.2 kW, than when it is 3.6 kW. For example, the daily idle capacity for private CPs during weekdays is 2.3 times higher with the 7.2 kW charging capacity than it is with the 3.6 kW charging capacity. Also in Fig. 17, the daily charging load profiles are based on the period with 30 to 82 users, with the number of users using private CPs is increasing from 18 to 58, and users using shared CPs are increasing from 12 to 24. In the Appendix, Figs. A4–A7 shows the same figures also for Saturdays and Sundays. The weekend data show that the charging demand is higher on Sundays than on Saturdays. This is as expected in Norway, since there is a culture for travelling during the weekends. For private CPs, the average idle capacity is nearly double from 09:00 to 16:00 during the weekends, compared to during the week, since more cars are parked then.

Average profiles give a quick overview of the flexibility potential, but since idle capacity is connected to the individual cars, the poten-

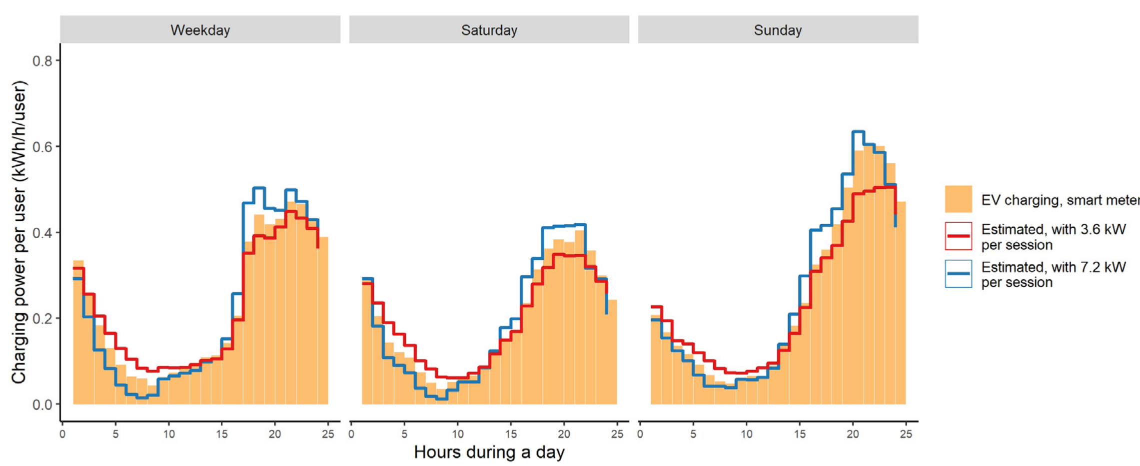

Fig. 13. Synthetic daily average charging load profiles per user, during weekdays and weekends. (Based on data with 57 users on average, using both private and shared CPs).

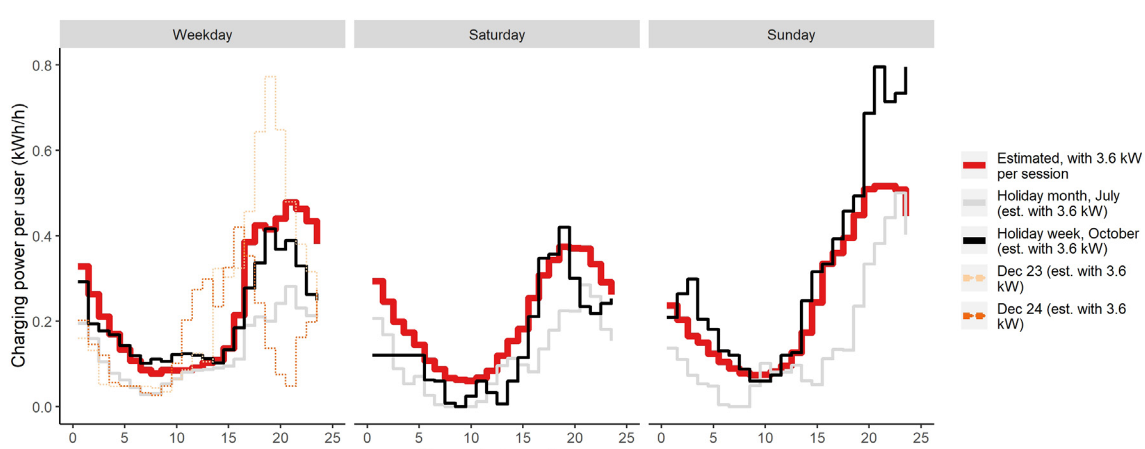

Fig. 14. Synthetic daily charging load profiles per user, for the aggregated EV charging during weekdays and weekends, showing annual average (red line) and holiday periods (black/grey/orange lines), assuming a charging power of 3.6 kW. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

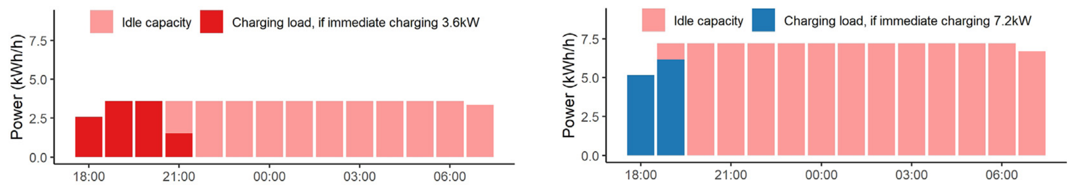

Fig. 15. Single charging session. Charging load and idle capacity, assuming charging power 3.6 (left) or 7.2 kW (right).

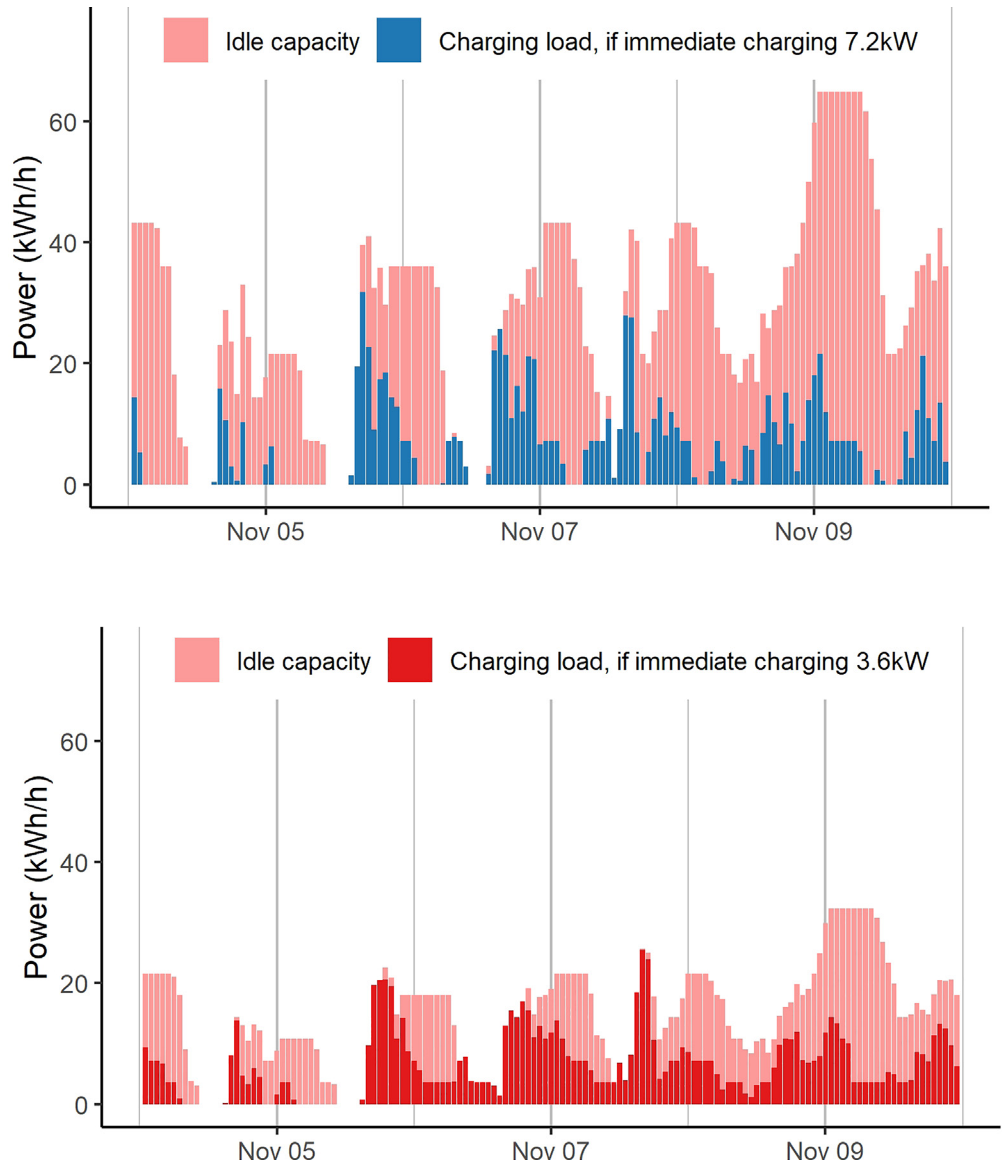

Fig. 16. EV charging in garage Bl2 during a week. Aggregated charging load and idle capacity, assuming charging power 3.6 (left) or 7.2 kW (right).

tial for moving charging loads in time depends on the length of the individual charging sessions. Average aggregated loads and idle capacity do not contain such information. Table A1 in the Appendix provides additional insights into the charging habits and non-charging idle times for private CPs during weekdays. The table is based on 3278 charging sessions during a data period with an average of 45 users (increase from 18 to 58 users). The orange column with hourly charging loads, is especially useful e.g. when estimating charging needs in building estates. The share with idle times can be read as following: e.g. during daily hour 03:00–04:00, all of the charging load can be charged (0.06 kWh/user), but none of charging has to happen immediately (50% can be delayed 1 to 2 h and 50% 7 to 8 h). If desired, also the charging load in the hour before can be delayed and charged during this hour (0.09 kWh/user), as well as other energy loads marked green from previous hours (total 3.9 kWh/user), limited by the maximum charging load during the hour in the blue column (2.65 kWh/user). The capacities and loads are presented per user, and should therefore be multiplied by the number of registered EV users in an apartment building or garage. Also in the Appendix, Table A2 provides a table with corresponding data for weekends, based on 1096 charging sessions and on average 44 users. Table A3 and Table A4 contain information from the shared CPs, based on 905 charging sessions during the weekdays, 407 charging sessions during the weekends, and

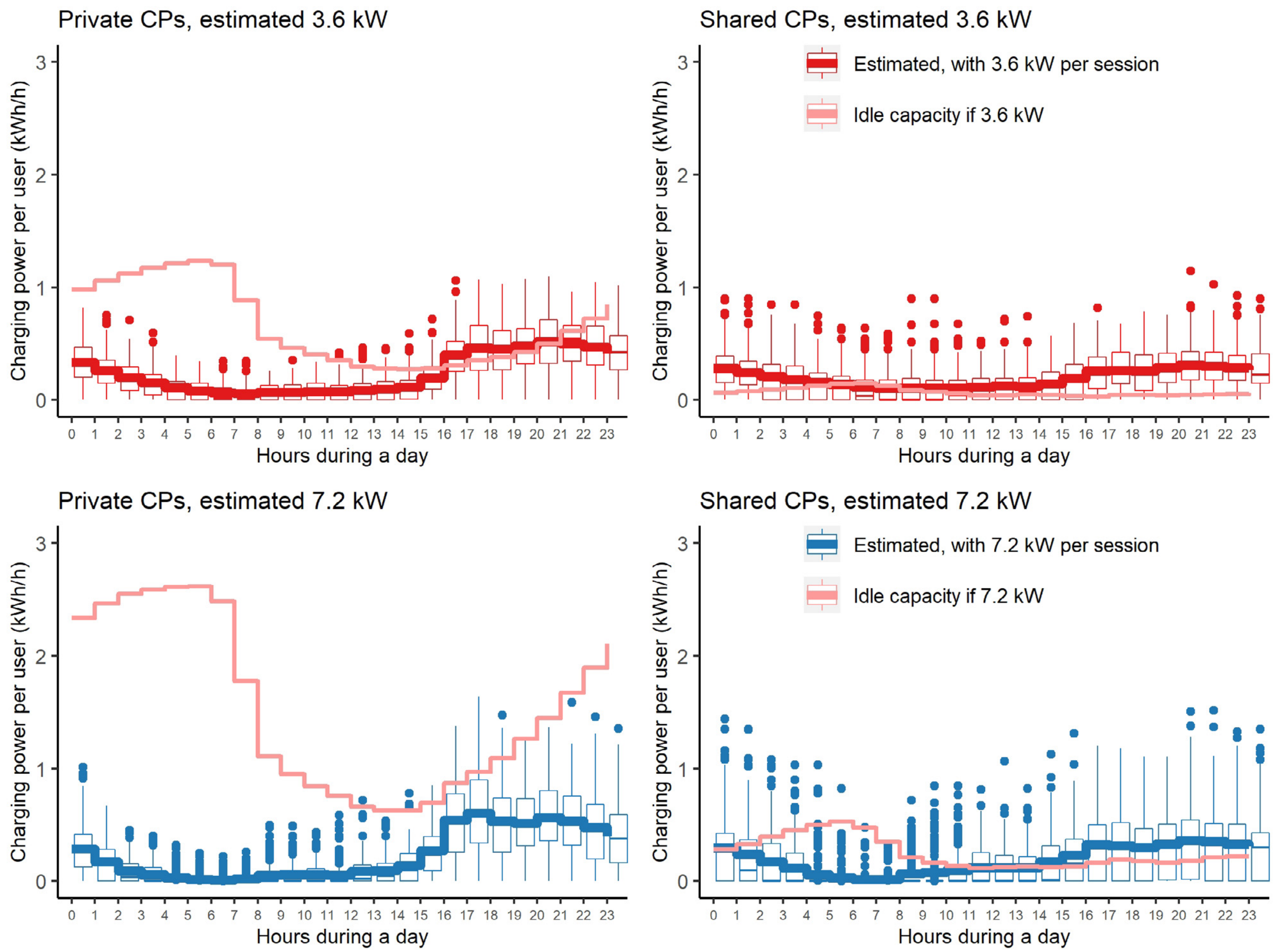

Fig. 17. Synthetic daily average charging load profiles and idle capacity profiles per user, showing private CPs (left) and shared CPs (right), with estimated charging power 3.6 kW (top) or 7.2 kW (bottom).

on average 18 users. In practice, to fully utilize the flexibility potential, it is necessary to know the expected connection times of the residents, as well as the required energy to be charged. This requires information from the users themselves (expected connection times) and energy or battery status information, preferably from the car to the charger.

5. Conclusions and future work

To prevent EV charging from having a negative impact on the power grid, it is essential to understand EV charging behaviour in different situations and premises. The literature review has identified a gap, with few studies analysing real data from residential EV charging in apartment buildings. This study proposes a methodology for using EV charging reports to describe charging habits, electricity load profiles, and flexibility potential of EV charging. The required input data are generally available for apartment buildings in Norway, which makes wide scale use of the methodology possible. Moreover, there is no need for new logging equipment or personal information about the residents. It is also possible to use the methodology for building categories other than apartment buildings. Data and hourly predictions from this study are available for other research groups.

The EV charging reports are used as a basis to describe EV charging habits for residents. Field data from a large housing cooperative in Norway are analysed in the case study, with 6878 EV charging sessions registered by 97 user IDs. The study finds a difference in residential charging habits when users have private CPs at their own parking space, compared to when they use a shared CP. For private CPs, the average connection time is 12.8 h, while it is 6.5 h for shared CPs. The average connection time for charged CPs is similar to the value for publicly accessible CPs found by [26], where the average was 7 h. The users with private CPs have on average 4.4 charging sessions per week, which is about 3.5 times more frequently than the users with shared CPs. There is a longer non-charging idle time for private charging sessions, which results in a higher potential for flexibility.

A correlation is found between plug-in/plug-out times and local hourly traffic data, thus providing possibilities for improved planning and simulation of residential charging. The authors aim to study this correlation more explicitly in future work, with EV charging reports and traffic data from more locations. The correlation can be part of a new model for EV charging loads and flexibility.

Information about energy and plug-in times from the EV charging reports are translated into hourly energy charging, assuming two different levels of charging power. The study compares the two charging power assumptions of 3.6 kW and 7.2 kW, respectively. In real life, EVs in a garage typically have a mix of charging power levels. By combining a lower and a higher charging power assumption when calculating the synthetic charging load, the true load can be expected to lie between the two synthetic levels.

Non-charging idle times are translated into energy flexibility potential, or *idle capacity*. While the daily average charging load profiles are similar for the two charging capacities, the average idle capacity differs, with higher values when the charging capacity is 7.2 kW, than when charging capacity is 3.6 kW. For example, the average idle capacity for private CPs during weekdays is 2.3 times higher with the 7.2 kW charging capacity than with the 3.6 kW charging capacity. The study provides tabulated values for additional insights into charging habits and non-charging idle times for private and shared CPs, for weekdays and weekends.

The study finds a significant potential for residential EV charging flexibility when private parking spaces have a CP. Also, the results support the theory that EV charging is a main source of flexible electricity use in apartment buildings. This is an important take-away for policy and decision makers, which can provide incentives for CPs at private parking spaces, as well as for charging energy management systems.

CRediT authorship contribution statement

A.L. Sørensen: Conceptualization, Methodology, Investigation, Data curation, Writing - original draft, Writing - review & editing. **K.B. Lindberg:** Conceptualization, Writing - review & editing, Supervision. **I. Sartori:** Conceptualization, Writing - review & editing, Supervision. **I. Andresen:** Conceptualization, 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.

Acknowledgements

The work presented in this paper was developed within the Institute PhD grant (272402) at SINTEF, financed by the Research Council of Norway. Contributions from Risvollan housing cooperative, EV owners in Risvollan, NTE Marked, TrønderEnergi Nett, ZapTec, Enoco, Fosen Innovasjon and Meshcrafts are highly appreciated. The study is part of the Research Centre on Zero Emission Neighbourhoods in Smart Cities (FME ZEN). The authors gratefully acknowledge the support from the ZEN partners and the Research Council of Norway. A sincere thank you to Nancy Eik-Nes for proofreading the manuscript.

Appendix

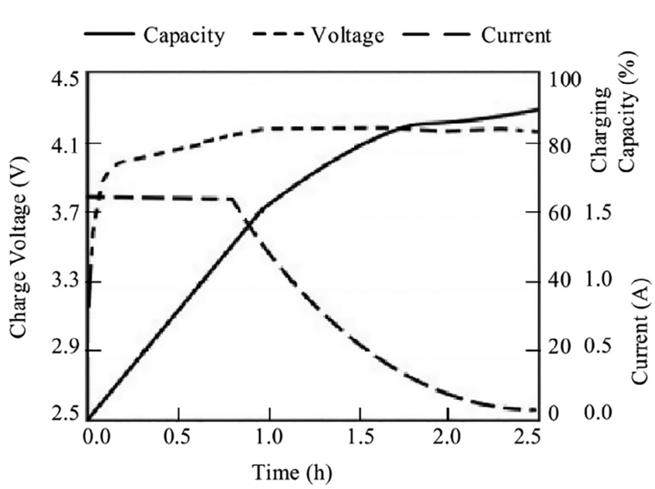

Fig. A1. Typical characteristics of the lithium-ion battery charging, from [42].

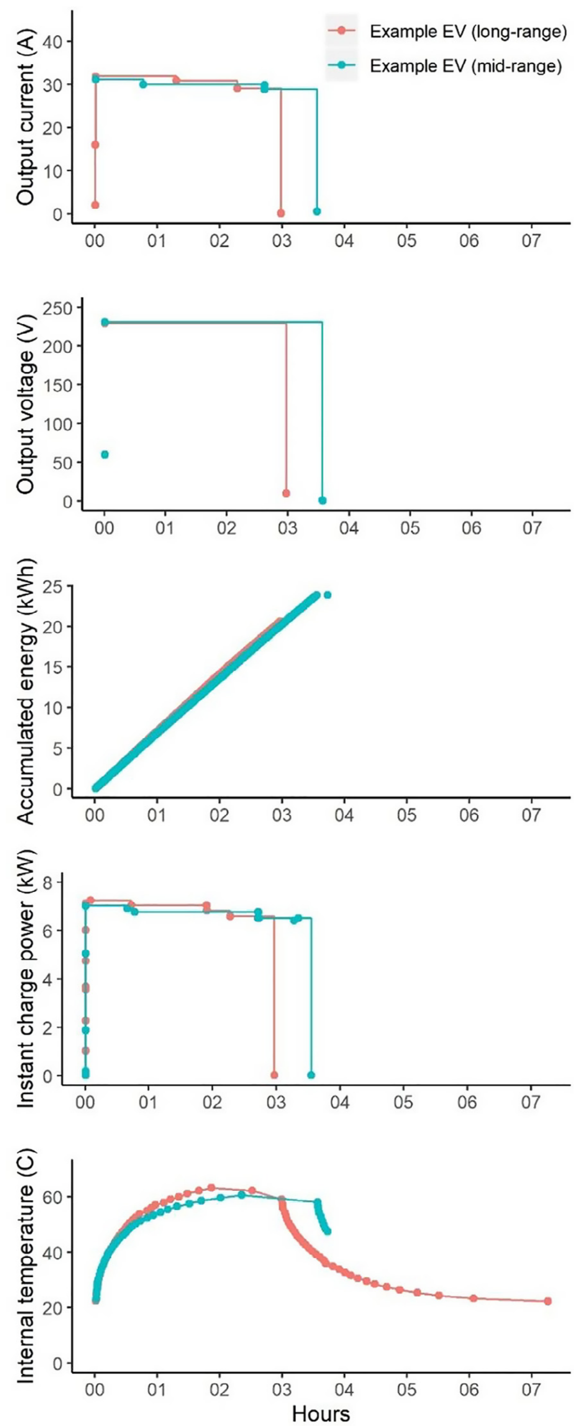

Fig. A2. Examples of charging characteristics of EV batteries from two charging sessions in the case study. Nominal charging power of the mid-range EV is 7.2 kW (session 943, user Bl2-4), while the long-range EV is limited by the available AC power of 7.4 kW (session 1158, user Bl2-3).

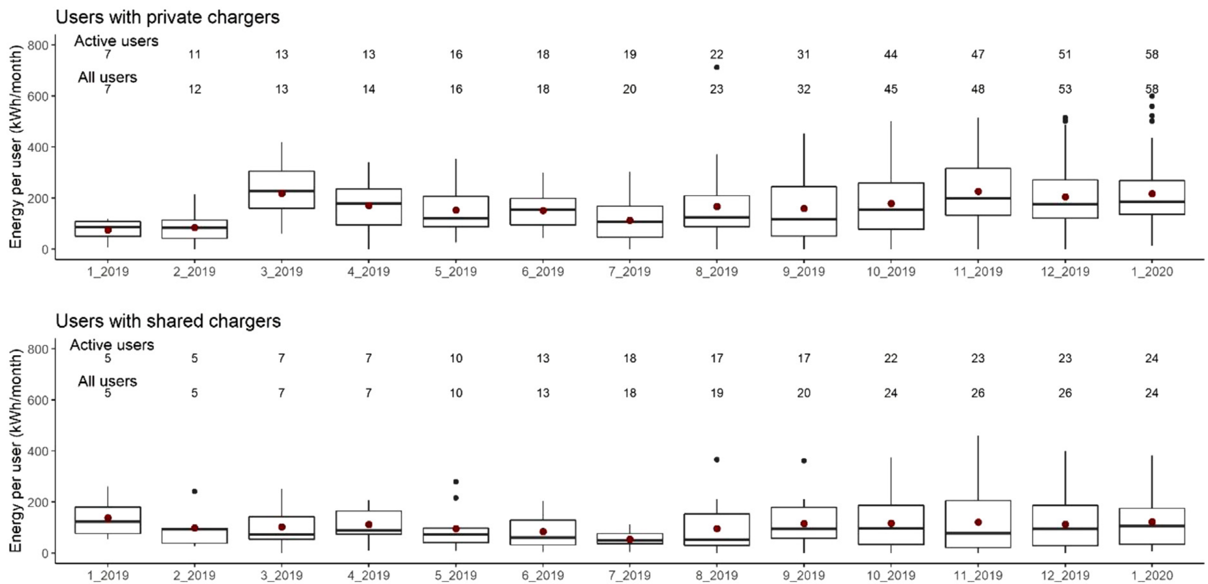

Fig. A3. Boxplots for monthly energy charged per user, divided according to users with private or shared CPs.

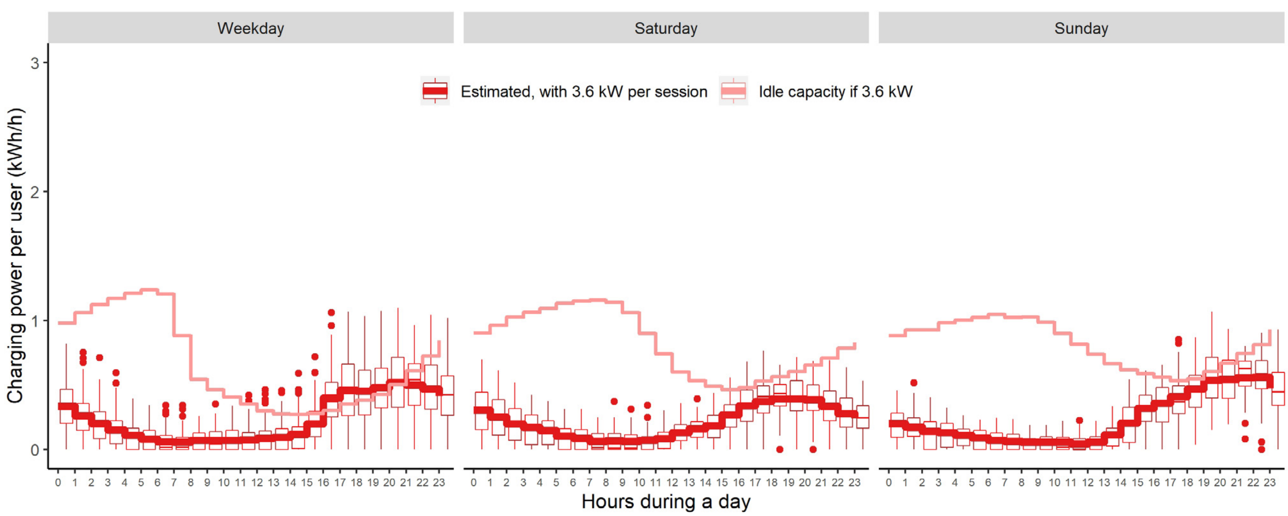

Fig. A4. Private CPs with estimated charging power 3.6 kW: Synthetic daily average charging load profiles and idle capacity profiles per user (data with 18 to 58 users).

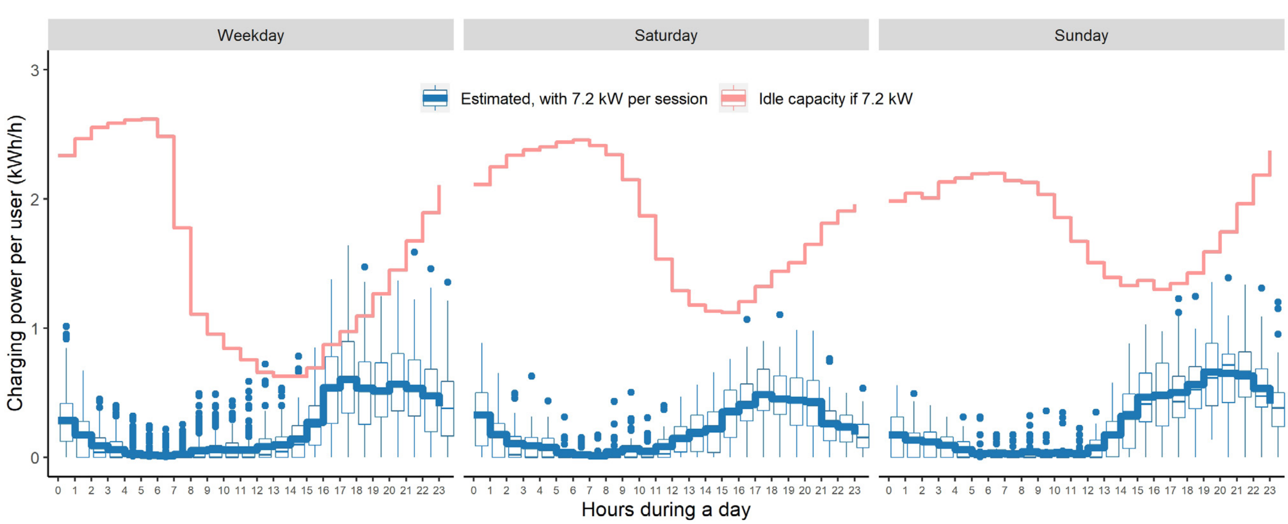

Fig. A5. Private CPs with estimated charging power 7.2 kW: Synthetic daily average charging load profiles and idle capacity profiles per user (data with 18 to 58 users).

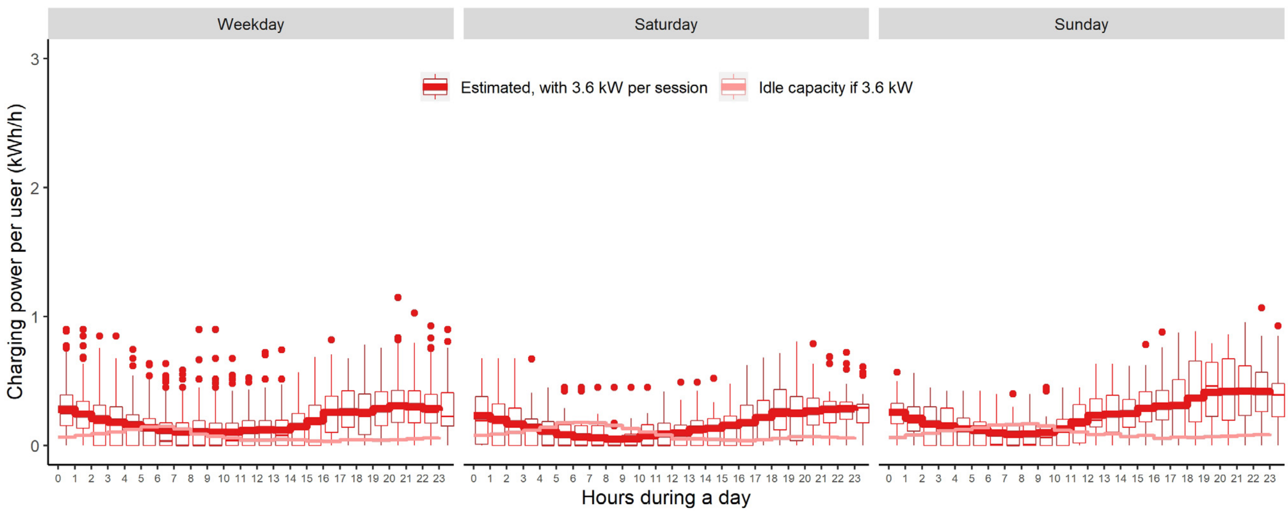

Fig. A6. Shared CPs with estimated charging power 3.6 kW: Synthetic daily average charging load profiles and idle capacity profiles per user (data with 12 to 24 users).

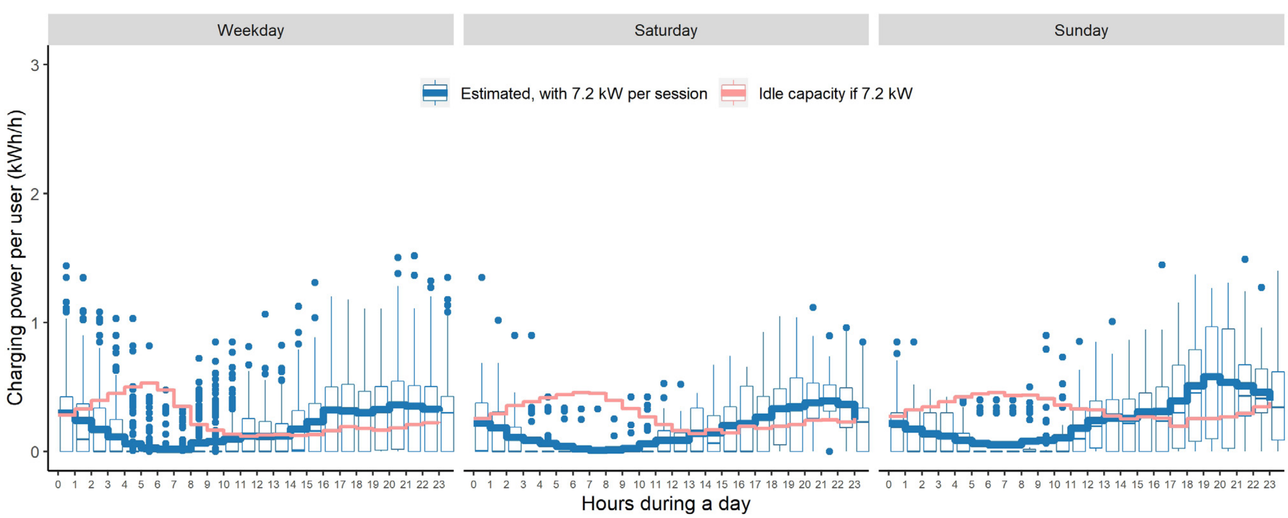

Fig. A7. Shared CPs with estimated charging power 7.2 kW: Synthetic daily average charging load profiles and idle capacity profiles per user (data with 12 to 24 users).

Table A1
Private CPs during weekdays: Average hourly charging load and idle capacity per user and share of plug-in, plug-out and non-charging idle times. Estimated charging power is 7.2 kW.

Daily hour	Share plug-in (% / h)	Share plug-out (% / h)	Available charging capacity *, if perfect foresight (kWh/h/user) * Sum of charging load and idle capacity	Charging load, if immediate charging (kWh/h/user)	Share with idle time of # hours														
					<1	1<2	2<3	3<4	4<5	5<6	6<7	7<8	8<9	9<10	10<11	11<12	12 < 18	18 ≤	
00 - 01	0.8 %	0.3 %	2.62	0.28	4 %	4 %	4 %	NA	8 %	27 %	19 %	8 %	8 %	8 %	8 %	4 %	NA	NA	100%
01 - 02	0.3 %	0.2 %	2.64	0.17	NA	NA	9 %	NA	9 %	NA	9 %	18 %	9 %	NA	NA	NA	27 %	18 %	100%
02 - 03	0.2 %	0.1 %	2.64	0.09	NA	NA	20 %	40 %	NA	NA	NA	NA	NA	NA	NA	NA	20 %	20 %	100%
03 - 04	0.1 %	0.2 %	2.65	0.06	NA	50 %	NA	NA	NA	NA	NA	50 %	NA	NA	NA	NA	NA	NA	100%
04 - 05	0.0 %	0.0 %	2.64	0.03	NA	NA	NA	NA	100 %	NA	NA	NA	NA	NA	NA	NA	NA	NA	100%
05 - 06	0.1 %	7.1 %	2.63	0.02	100 %	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	100%
06 - 07	0.3 %	22.5 %	2.49	0.01	11 %	22 %	NA	11 %	NA	22 %	NA	22 %	NA	NA	NA	NA	NA	11 %	100%
07 - 08	1.2 %	8.2 %	1.80	0.02	45 %	5 %	5 %	5 %	13 %	5 %	5 %	3 %	3 %	NA	3 %	NA	3 %	5 %	100%
08 - 09	1.2 %	4.8 %	1.18	0.05	33 %	15 %	13 %	3 %	10 %	5 %	10 %	NA	NA	3 %	3 %	NA	NA	8 %	100%
09 - 10	0.8 %	4.5 %	1.03	0.06	24 %	8 %	16 %	4 %	16 %	NA	NA	8 %	4 %	NA	NA	NA	NA	20 %	100%
10 - 11	1.3 %	5.8 %	0.93	0.06	42 %	14 %	12 %	NA	2 %	NA	2 %	2 %	NA	NA	NA	NA	NA	26 %	100%
11 - 12	1.6 %	4.3 %	0.85	0.06	30 %	23 %	4 %	11 %	4 %	4 %	2 %	2 %	NA	NA	NA	NA	6 %	15 %	100%
12 - 13	2.3 %	3.3 %	0.79	0.09	26 %	16 %	6 %	3 %	6 %	3 %	5 %	3 %	NA	NA	NA	NA	6 %	26 %	100%
13 - 14	2.9 %	3.6 %	0.76	0.10	31 %	11 %	7 %	7 %	6 %	1 %	1 %	NA	1 %	NA	NA	2 %	5 %	27 %	100%
14 - 15	4.7 %	3.6 %	0.81	0.15	29 %	10 %	13 %	3 %	2 %	1 %	NA	1 %	NA	1 %	NA	NA	16 %	24 %	100%
15 - 16	12.2 %	4.9 %	0.98	0.27	21 %	18 %	9 %	3 %	1 %	1 %	0 %	0 %	1 %	0 %	0 %	1 %	27 %	19 %	100%
16 - 17	18.3 %	8.4 %	1.41	0.54	30 %	10 %	4 %	2 %	2 %	0 %	1 %	0 %	1 %	1 %	0 %	3 %	34 %	12 %	100%
17 - 18	8.6 %	6.2 %	1.57	0.60	25 %	5 %	4 %	2 %	1 %	0 %	1 %	NA	1 %	1 %	4 %	7 %	33 %	17 %	100%
18 - 19	7.9 %	4.5 %	1.63	0.54	17 %	5 %	1 %	2 %	0 %	2 %	2 %	2 %	0 %	5 %	10 %	15 %	29 %	10 %	100%
19 - 20	10.6 %	3.3 %	1.78	0.51	16 %	5 %	2 %	1 %	2 %	2 %	1 %	2 %	3 %	9 %	19 %	13 %	17 %	8 %	100%
20 - 21	9.4 %	2.4 %	2.03	0.57	8 %	3 %	2 %	1 %	0 %	3 %	3 %	6 %	6 %	21 %	16 %	4 %	18 %	10 %	100%
21 - 22	6.9 %	1.3 %	2.22	0.54	3 %	0 %	NA	NA	1 %	3 %	6 %	11 %	22 %	19 %	8 %	7 %	12 %	8 %	100%
22 - 23	5.7 %	0.6 %	2.37	0.48	2 %	2 %	1 %	1 %	4 %	4 %	9 %	17 %	27 %	7 %	5 %	4 %	13 %	4 %	100%
23 - 24	2.6 %	0.3 %	2.50	0.40	3 %	1 %	NA	6 %	2 %	14 %	17 %	13 %	6 %	13 %	6 %	3 %	9 %	6 %	100%
Total	100 %	100 %	42.9	5.7															

Table A2
Private CPs during weekends: Average hourly charging load and idle capacity per user and share of plug-in, plug-out and non-charging idle times. Estimated charging power is 7.2 kW.

Daily hour	Shareplug-in (%/h)	Shareplug-out (%/h)	Available charging capacity *, if perfect foresight (kWh/h/user)* Sum of charging load and idle capacity	Charging load, if immediate charging (kWh/h/user)	Share with idle time of # hours														
					<1	1 < 2	2 < 3	3 < 4	4 < 5	5 < 6	6 < 7	7 < 8	8 < 9	9 < 10	10 < 11	11 < 12	12 < 18	18 ≤	
00–01	2.3%	0.6%	2.34	0.26	8%	*NA*	*NA*	*NA*	12%	4%	*NA*	4%	12%	16%	12%	4%	28%	*NA*	100%
01–02	1.4%	0.7%	2.34	0.16	7%	*NA*	*NA*	*NA*	*NA*	7%	7%	20%	7%	*NA*	7%	27%	20%	*NA*	100%
02–03	0.7%	0.2%	2.36	0.12	*NA*	*NA*	*NA*	*NA*	*NA*	25%	13%	25%	*NA*	*NA*	13%	*NA*	25%	*NA*	100%
03–04	0.7%	0.1%	2.38	0.09	13%	13%	*NA*	*NA*	13%	*NA*	*NA*	13%	38%	*NA*	*NA*	*NA*	13%	*NA*	100%
04–05	0.2%	0.3%	2.39	0.07	50%	*NA*	*NA*	*NA*	*NA*	50%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
05–06	0.4%	0.3%	2.39	0.03	25%	*NA*	25%	*NA*	*NA*	25%	*NA*	25%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
06–07	0.5%	6.7%	2.39	0.03	*NA*	*NA*	*NA*	20%	*NA*	*NA*	20%	20%	20%	*NA*	*NA*	*NA*	*NA*	20%	100%
07–08	0.5%	17.6%	2.33	0.02	17%	17%	33%	*NA*	17%	*NA*	17%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
08–09	0.7%	5.3%	2.31	0.04	38%	13%	13%	38%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
09–10	0.8%	5.7%	2.18	0.05	44%	11%	*NA*	*NA*	*NA*	22%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	22%	100%
10–11	1.1%	6.1%	1.93	0.04	25%	25%	8%	*NA*	*NA*	8%	*NA*	8%	8%	*NA*	*NA*	*NA*	*NA*	17%	100%
11–12	2.3%	5.5%	1.69	0.06	40%	16%	8%	*NA*	*NA*	8%	*NA*	*NA*	8%	*NA*	*NA*	*NA*	4%	16%	100%
12–13	4.4%	5.1%	1.53	0.11	25%	13%	15%	*NA*	6%	*NA*	2%	*NA*	2%	*NA*	*NA*	4%	10%	23%	100%
13–14	7.5%	5.5%	1.47	0.18	18%	15%	10%	7%	2%	2%	*NA*	*NA*	*NA*	*NA*	1%	*NA*	10%	34%	100%
14–15	8.0%	4.9%	1.53	0.28	18%	13%	7%	6%	1%	3%	1%	*NA*	2%	1%	*NA*	*NA*	23%	25%	100%
15–16	11.8%	5.2%	1.65	0.41	16%	9%	4%	5%	4%	2%	*NA*	1%	1%	2%	2%	2%	22%	30%	100%
16–17	8.8%	5.7%	1.70	0.44	19%	9%	4%	2%	1%	*NA*	1%	1%	1%	2%	2%	2%	27%	28%	100%
17–18	10.4%	6.9%	1.86	0.50	17%	4%	4%	4%	2%	3%	1%	1%	*NA*	2%	4%	4%	36%	19%	100%
18–19	9.9%	5.7%	1.94	0.51	11%	6%	1%	2%	1%	2%	2%	3%	4%	6%	6%	6%	29%	21%	100%
19–20	8.9%	3.7%	2.10	0.55	8%	4%	1%	4%	2%	1%	*NA*	3%	2%	7%	11%	11%	26%	19%	100%
20–21	6.2%	2.5%	2.24	0.54	7%	3%	3%	3%	6%	3%	3%	*NA*	4%	12%	16%	4%	16%	19%	100%
21–22	4.7%	2.8%	2.37	0.45	6%	4%	2%	*NA*	2%	2%	8%	4%	10%	29%	8%	*NA*	16%	10%	100%
22–23	5.0%	1.8%	2.47	0.39	7%	2%	*NA*	*NA*	2%	5%	4%	16%	11%	15%	2%	13%	16%	7%	100%
23–24	2.9%	1.1%	2.50	0.30	6%	6%	*NA*	3%	*NA*	13%	3%	16%	9%	6%	13%	3%	22%	*NA*	100%
Total	100%	100%	50.4	5.6															

Table A3
Shared CPs during weekdays: Average hourly charging load and idle capacity per user and share of plug-in, plug-out and non-charging idle times. Estimated charging power is 7.2 kW.

Daily hour	Shareplug-in (%/h)	Shareplug-out (%/h)	Available charging capacity *, if perfect foresight (kWh/h/user)* Sum of charging load and idle capacity	Charging load, if immediate charging (kWh/h/user)	Share with idle time of # hours														
					<1	1 < 2	2 < 3	3 < 4	4 < 5	5 < 6	6 < 7	7 < 8	8 < 9	9 < 10	10 < 11	11 < 12	12 < 18	18 ≤	
00–01	1.3%	1.9%	0.44	0.21	8%	*NA*	*NA*	33%	8%	17%	17%	*NA*	8%	*NA*	8%	*NA*	*NA*	*NA*	100%
01–02	0.3%	1.0%	0.45	0.16	*NA*	*NA*	*NA*	33%	33%	33%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
02–03	0.2%	0.4%	0.46	0.12	*NA*	*NA*	*NA*	*NA*	50%	*NA*	*NA*	*NA*	*NA*	*NA*	50%	*NA*	*NA*	*NA*	100%
03–04	*NA*	0.1%	0.47	0.08	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
04–05	0.1%	0.1%	0.47	0.04	*NA*	*NA*	100%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
05–06	0.2%	0.6%	0.47	0.02	50%	50%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
06–07	0.1%	6.2%	0.43	0.01	100%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
07–08	2.0%	8.3%	0.31	0.01	72%	*NA*	17%	*NA*	*NA*	6%	*NA*	6%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
08–09	2.3%	5.2%	0.25	0.05	76%	*NA*	*NA*	5%	*NA*	10%	5%	5%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
09–10	1.5%	2.7%	0.24	0.07	71%	7%	*NA*	*NA*	14%	7%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
10–11	2.9%	4.1%	0.22	0.09	35%	23%	27%	12%	4%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
11–12	4.0%	3.9%	0.22	0.11	39%	22%	11%	17%	3%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	8%	100%
12–13	3.4%	3.3%	0.25	0.13	45%	26%	16%	3%	6%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	3%	100%
13–14	4.5%	2.5%	0.25	0.13	44%	27%	17%	5%	*NA*	2%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	2%	2%	100%
14–15	8.2%	5.0%	0.27	0.16	36%	36%	14%	4%	3%	1%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	4%	1%	100%
15–16	11.0%	5.9%	0.28	0.18	65%	16%	8%	4%	2%	*NA*	1%	*NA*	*NA*	1%	*NA*	*NA*	2%	1%	100%
16–17	10.4%	4.3%	0.37	0.27	60%	17%	3%	2%	2%	4%	2%	1%	*NA*	2%	*NA*	1%	4%	1%	100%
17–18	6.9%	8.8%	0.37	0.24	37%	19%	13%	6%	2%	*NA*	3%	*NA*	2%	*NA*	3%	3%	10%	2%	100%
18–19	8.0%	8.4%	0.36	0.22	50%	8%	8%	1%	4%	8%	*NA*	1%	4%	6%	*NA*	1%	6%	1%	100%
19–20	10.6%	6.2%	0.37	0.24	26%	10%	8%	5%	6%	8%	5%	4%	7%	2%	3%	3%	8%	2%	100%
20–21	8.3%	5.4%	0.42	0.28	20%	15%	11%	11%	4%	4%	7%	9%	4%	1%	5%	*NA*	8%	1%	100%
21–22	5.6%	6.0%	0.44	0.27	6%	16%	16%	12%	6%	2%	10%	8%	4%	8%	4%	2%	8%	*NA*	100%
22–23	5.2%	5.5%	0.43	0.26	6%	6%	4%	11%	9%	4%	9%	9%	17%	15%	6%	*NA*	4%	*NA*	100%
23–24	2.9%	4.3%	0.42	0.24	4%	*NA*	8%	12%	8%	8%	23%	8%	19%	4%	8%	*NA*	*NA*	*NA*	100%
Total	100%	100%	8.7	3.6															

Table A4
Shared CPs during weekends: Average hourly charging load and idle capacity per user and share of plug-in, plug-out and non-charging idle times. Estimated charging power is 7.2 kW.

Daily hour	Share plug-in (%/h)	Share plug-out (%/h)	Available charging capacity *, if perfect foresight (kWh/h/user) * Sum of charging load and idle capacity	Charging load, if immediate charging (kWh/h/user)	Share with idle time of # hours														
					<1	1 < 2	2 < 3	3 < 4	4 < 5	5 < 6	6 < 7	7 < 8	8 < 9	9 < 10	10 < 11	11 < 12	12 < 18	18 ≤	
00–01	3.4%	0.5%	0.38	0.20	*NA*	*NA*	36%	*NA*	7%	7%	7%	14%	7%	7%	*NA*	*NA*	14%	*NA*	100%
01–02	0.2%	0.5%	0.39	0.17	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
02–03	*NA*	0.2%	0.39	0.12	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
03–04	0.5%	0.2%	0.39	0.09	*NA*	*NA*	*NA*	50%	50%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
04–05	*NA*	*NA*	0.41	0.07	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
05–06	*NA*	0.7%	0.41	0.05	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
06–07	*NA*	4.2%	0.41	0.03	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
07–08	*NA*	5.2%	0.39	0.02	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
08–09	1.5%	3.9%	0.38	0.03	67%	*NA*	*NA*	33%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
09–10	2.0%	4.9%	0.34	0.05	25%	50%	*NA*	*NA*	*NA*	13%	13%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
10–11	4.4%	3.9%	0.30	0.06	22%	28%	22%	6%	*NA*	6%	6%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	11%	100%
11–12	5.9%	5.4%	0.29	0.09	54%	17%	8%	8%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	13%	100%
12–13	6.9%	3.4%	0.29	0.11	46%	29%	4%	7%	*NA*	4%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	7%	4%	100%
13–14	5.9%	7.4%	0.32	0.15	38%	25%	13%	*NA*	*NA*	4%	*NA*	*NA*	*NA*	4%	*NA*	*NA*	8%	8%	100%
14–15	9.1%	4.9%	0.33	0.14	46%	19%	11%	5%	3%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	16%	*NA*	100%
15–16	9.1%	7.9%	0.36	0.18	38%	32%	8%	*NA*	3%	*NA*	3%	3%	*NA*	*NA*	*NA*	3%	8%	3%	100%
16–17	6.6%	7.1%	0.38	0.18	52%	19%	*NA*	7%	*NA*	*NA*	*NA*	*NA*	4%	*NA*	4%	*NA*	15%	*NA*	100%
17–18	12.3%	6.1%	0.38	0.21	46%	6%	12%	2%	2%	*NA*	8%	4%	4%	*NA*	2%	4%	4%	6%	100%
18–19	9.3%	5.9%	0.46	0.26	47%	18%	3%	5%	*NA*	5%	3%	3%	*NA*	*NA*	3%	*NA*	13%	*NA*	100%
19–20	6.1%	5.9%	0.50	0.30	40%	12%	20%	4%	4%	*NA*	*NA*	8%	*NA*	4%	4%	4%	*NA*	*NA*	100%
20–21	5.4%	5.7%	0.48	0.27	36%	9%	*NA*	*NA*	*NA*	5%	*NA*	5%	*NA*	14%	5%	5%	23%	*NA*	100%
21–22	5.9%	5.7%	0.47	0.27	17%	8%	8%	*NA*	8%	13%	4%	13%	8%	4%	4%	*NA*	13%	*NA*	100%
22–23	3.4%	6.4%	0.45	0.25	7%	7%	*NA*	*NA*	*NA*	*NA*	14%	36%	14%	7%	*NA*	7%	7%	*NA*	100%
23–24	2.0%	3.9%	0.43	0.22	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	25%	25%	*NA*	*NA*	13%	25%	13%	*NA*	100%
Total	100%	100%	9.3	3.5															

References

[1] IEA, Global EV Outlook 2020, OECD Publishing, Paris, France, 2020. https://doi.org/10.1787/9789264302365-en.
[2] Norwegian EV Association, Elbilisten 2019 (Annual questionnaire), (2019).
[3] Norwegian Government, Regjeringen foreslår å gi beboere i borettslag rett til å lade hjemme, (2019).
[4] Å.L. Sørensen, I. Sartori, I. Andresen, D. Johansson, H. Bagge, Å. Wahlström, Smart EV Charging Systems to Improve Energy Flexibility of Zero Emission Neighbourhoods, in: Cold Clim. HVAC 2018, Springer International Publishing, Cham, 2019: pp. 467–477. https://doi.org/10.1007/978-3-030-00662-4_39.
[5] Yongbao Chen, Peng Xu, Jiefan Gu, Ferdinand Schmidt, Weilin Li, Measures to improve energy demand flexibility in buildings for demand response (DR): A review, Energy and Buildings 177 (2018) 125–139, https://doi.org/10.1016/j.enbuild.2018.08.003.
[6] Åse Lekang Sørensen, Igor Sartori, Karen Byskov Lindberg, Inger Andresen, Electricity analysis for energy management in neighbourhoods: Case study of a large housing cooperative in Norway, J. Phys.: Conf. Ser. 1343 (2019) 012057, https://doi.org/10.1088/1742-6596/1343/1/012057.
[7] M. Beaudin, H. Zareipour, Home energy management systems: A review of modelling and complexity, Lect. Notes Energy. 33 (2017) 753–793, https://doi.org/10.1007/978-3-319-26950-4_35.
[8] Peter D. Lund, Juuso Lindgren, Jani Mikkola, Jyri Salpakari, Review of energy system flexibility measures to enable high levels of variable renewable electricity, Renewable and Sustainable Energy Reviews 45 (2015) 785–807, https://doi.org/10.1016/j.rser.2015.01.057.
[9] K. Knezovic, Active integration of electric vehicles in the distribution network - theory, modelling and practice, DTU - Technical University of Denmark, Risø, Roskilde, Denmark, 2016.
[10] R. D'hulst, W. Labeeuw, B. Beusen, S. Claessens, G. Deconinck, K. Vanthournout, Demand response flexibility and flexibility potential of residential smart appliances: Experiences from large pilot test in Belgium, Applied Energy 155 (2015) 79–90, https://doi.org/10.1016/j.apenergy.2015.05.101.
[11] M. Noussan, F. Neirotti, Cross-Country Comparison of Hourly Electricity Mixes for EV Charging Profiles, Energies 13 (10) (2020), https://doi.org/10.3390/en13102527.
[12] J.R. Helmus, M.H. Lees, R. van den Hoed, A data driven typology of electric vehicle user types and charging sessions, Transp. Res. Part C Emerg. Technol. 115 (2020), https://doi.org/10.1016/j.trc.2020.102637 102637.
[13] The Norwegian Water Resources and Energy Directorate (NVE), Kostnader i strømnettet - gevinster ved koordinert lading av elbiler, Oslo, Norway, 2019.
[14] European Union, Directive of 2009/72/EC of the European Parliament and of the Council of 13 July 2009 Concerning Common Rules for the Internal Market in Electricity and Repealing Directive 2003/54/EC, Off. J. Eur. Union. L211 (2009) L 211/55-L 211/93. https://doi.org/10.1126/science.202.4366.409.
[15] D. Fischer, A. Harbrecht, A. Surmann, R. McKenna, Electric vehicles' impacts on residential electric local profiles – A stochastic modelling approach considering socio-economic, behavioural and spatial factors, Appl. Energy. 233–234 (2019) 644–658, https://doi.org/10.1016/j.apenergy.2018.10.010.
[16] S. Babrowski, H. Heinrichs, P. Jochem, W. Fichtner, Load shift potential of electric vehicles in Europe, J. Power Sources. 255 (2014) 283–293, https://doi.org/10.1016/j.jpowsour.2014.01.019.
[17] K. Alanne, H. Liimatainen, Design implications of the electrification of passenger vehicle stock on renewable energy integration in Finnish apartment buildings, Sustain. Cities Soc. 47 (2019), https://doi.org/10.1016/j.scs.2019.101507 101507.
[18] D. Heinz, Erstellung und Auswertung repräsentativer Mobilitäts- und Ladeprofile für Elektrofahrzeuge in Deutschland, Work. Pap. Ser. Prod. Energy. (2018) 120, https://doi.org/10.5445/IR/1000086372.
[19] J. Brady, M. O'Mahony, Modelling charging profiles of electric vehicles based on real-world electric vehicle charging data, Sustain. Cities Soc. 26 (2016) 203–216, https://doi.org/10.1016/j.scs.2016.06.014.
[20] J. Schäuble, T. Kaschub, A. Ensslen, P. Jochem, W. Fichtner, Generating electric vehicle load profiles from empirical data of three EV fleets in Southwest Germany, J. Clean. Prod. 150 (2017) 253–266, https://doi.org/10.1016/j.jclepro.2017.02.150.
[21] P. Mesarić, S. Krajcar, Home demand side management integrated with electric vehicles and renewable energy sources, Energy Build. 108 (2015) 1–9, https://doi.org/10.1016/j.enbuild.2015.09.001.
[22] H. Saele, I. Petersen, Electric vehicles in Norway and the potential for demand response, Proc. - 2018 53rd Int. Univ. Power Eng. Conf. UPEC 2018. (2018). https://doi.org/10.1109/UPEC.2018.8541926.
[23] M.Z. Degefa, C. Andresen, Analysis of Future Loading Scenarios in a Norwegian LV Network, in: 2019 Int. Conf. Smart Energy Syst. Technol., Institute of Electrical and Electronics Engineers Inc., Porto, Portugal, 2019: pp. 1–6. https://doi.org/10.1109/SEST.2019.8849081.
[24] N. Sadeghianpourhamami, N. Refa, M. Strobbe, C. Develder, Quantitive analysis of electric vehicle flexibility: A data-driven approach, Int. J. Electr. Power Energy Syst. 95 (2018) 451–462, https://doi.org/10.1016/j.ijepes.2017.09.007.
[25] M.K. Gerritsma, T.A. Al Skaif, H.A. Fidder, W.G.J.H.M. van Sark, Flexibility of electric vehicle demand: Analysis of measured charging data and simulation for the future, World Electr, Veh. J. 10 (2019) 1–22, https://doi.org/10.3390/wevj10010014.
[26] M.G. Flammini, G. Prettico, A. Julea, G. Fulli, A. Mazza, G. Chicco, Statistical characterisation of the real transaction data gathered from electric vehicle charging stations, Electr. Power Syst. Res. 166 (2019) 136–150, https://doi.org/10.1016/j.epsr.2018.09.022.
[27] E. Xydas, C. Marmaras, L.M. Cipcigan, N. Jenkins, S. Carroll, M. Barker, A data-driven approach for characterising the charging demand of electric vehicles: A UK case study, Appl. Energy. 162 (2016) 763–771, https://doi.org/10.1016/j.apenergy.2015.10.151.
[28] J. Quirós-Tortós, L.F. Ochoa, B. Lees, A statistical analysis of EV charging behavior in the UK, 2015 IEEE PES Innov, Smart Grid Technol. Lat. Am. ISGT LATAM (2015. (2016)) 445–449, https://doi.org/10.1109/ISGT-LA.2015.7381196.
[29] M. Neaimeh, R. Wardle, A.M. Jenkins, J. Yi, G. Hill, P.F. Lyons, Y. Hübner, P.T. Blythe, P.C. Taylor, A probabilistic approach to combining smart meter and electric vehicle charging data to investigate distribution network impacts, Appl. Energy. 157 (2015) 688–698, https://doi.org/10.1016/j.apenergy.2015.01.144.
[30] Y.B. Khoo, C.H. Wang, P. Paevere, A. Higgins, Statistical modeling of Electric Vehicle electricity consumption in the Victorian EV Trial, Australia, Transp. Res. Part D Transp. Environ. 32 (2014) 263–277, https://doi.org/10.1016/j.trd.2014.08.017.
[31] E.C. Kara, J.S. Macdonald, D. Black, M. Bérges, G. Hug, S. Kiliccote, Estimating the benefits of electric vehicle smart charging at non-residential locations: A data-driven approach, Appl. Energy. 155 (2015) 515–525, https://doi.org/10.1016/j.apenergy.2015.05.072.
[32] H. Zhao, X. Yan, H. Ren, Quantifying flexibility of residential electric vehicle charging loads using non-intrusive load extracting algorithm in demand response, Sustain. Cities Soc. 50 (2019), https://doi.org/10.1016/j.scs.2019.101664 101664.
[33] J.D. Kim, Insights into residential EV charging behavior using energy meter data, Energy Policy. 129 (2019) 610–618, https://doi.org/10.1016/j.enpol.2019.02.049.
[34] V. Hoffmann, B.I. Fesche, K. Ingebrigtsen, I.N. Christie, M. Punnerud Engelstad, Automated Detection of Electric Vehicles in Hourly Smart Meter Data, in: CIRED Conf. Proc., AIM, Madrid, Spain, 2019: pp. 1–5.
[35] Å.L. Sørensen, K.B. Lindberg, H.T. Walnum, I. Sartori, U.R. Aakenes, I. Andresen, Heat analysis for energy management in neighbourhoods: Case study of a large housing cooperative in Norway, IOP Conf. Ser. Mater. Sci. Eng. (2019), https://doi.org/10.1088/1757-899X/609/5/052009.
[36] EV Database UK, Electric Vehicle Database, (2020). https://ev-database.uk/ (accessed April 16, 2020).
[37] Norwegian Electric Vehicle Association, Elbiler i dag, (2020). https://elbil.no/om-elbil/elbiler-idag/ (accessed April 16, 2020).
[38] E. Apostolaki-Iosifidou, P. Codani, W. Kempton, Measurement of power loss during electric vehicle charging and discharging, Energy. 127 (2017) 730–742, https://doi.org/10.1016/j.energy.2017.03.015.
[39] A. Kieldsen, A. Thingvad, S. Martinenas, T.M. Srensen, Efficiency test method for electric vehicle chargers, EVS 2016–29th Int, Electr. Veh, Symp, 2016.
[40] Y. Miao, P. Hynan, A. Von Jouanne, A. Yokochi, Current li-ion battery technologies in electric vehicles and opportunities for advancements, Energies. 12 (2019) 1–20, https://doi.org/10.3390/en12061074.
[41] Y. Li, J. Song, J. Yang, A review on structure model and energy system design of lithium-ion battery in renewable energy vehicle, Renew. Sustain. Energy Rev. 37 (2014) 627–633, https://doi.org/10.1016/j.rser.2014.05.059.
[42] M.A. Hannan, M.M. Hoque, A. Hussain, Y. Yusof, P.J. Ker, State-of-the-Art and Energy Management System of Lithium-Ion Batteries in Electric Vehicle Applications: Issues and Recommendations, IEEE Access. 6 (2018) 19362–19378, https://doi.org/10.1109/ACCESS.2018.2817655.
[43] Sony Corporation, Lithium Ion Rechargeable Batteries Technical Handbook, Tokyo, Japan, 2013.
[44] L. Lu, X. Han, J. Li, J. Hua, M. Ouyang, A review on the key issues for lithium-ion battery management in electric vehicles, J. Power Sources. 226 (2013) 272–288, https://doi.org/10.1016/j.jpowsour.2012.10.060.
[45] The R Foundation for Statistical Computing Platform, R version 3.6.2, (2019).
[46] Statens vegvesen, Trafikkdata, (2020). https://www.vegvesen.no/trafikkdata (accessed February 3, 2020).
[47] W.N. Venables, B.D. Ripley, Modern Applied Statistics with S, Fourth Edi, Springer-Verlag, New York (2002), https://doi.org/10.1007/978-0-387-21706-2.
[48] RDocumentation, Crosscorrelation Function CCF, (2020). https://www.rdocumentation.org/packages/tseries/versions/0.1-2/topics/ccf (accessed May 27, 2020).
[49] Statistics Norway, 12577: Kjørelengder, etter kjøretøytype, drivstofftype, statistikkvariabel og år, (2020). https://www.ssb.no/statbank/table/12577/tableViewLayout1/ (accessed March 26, 2020).
[50] L. Pedersen, Load Modelling of Buildings in Mixed Energy Distribution Systems. Doctoral Thesis., NTNU, 2007.