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Interruptibility in private electric vehicle charging: Case Finland

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Summary

Uncontrolled electric vehicle charging can increase peak loads and cause extra stress on the power system. By smartly controlling EV charging events, adversities caused by charging can be mitigated and charging loads can be utilized in different demand-side management schemes to support the power system on both local and grid levels. Electric vehicle charging events consist of the actual time spent charging and of idling, when the EV is connected to the EVSE but is not charging. This idling time can be utilized as an opportunity for load shifting or power reduction without compromising the charging outcome. This study analyses through simulation the interruptibility potential of Finnish private electric vehicle charging network. Based on the results roughly 70% of charging events can be interrupted for at least 10% of the time they are plugged-in to the EVSE.

Keywords: smart charging, load management, electric vehicle supply equipment (EVSE), electric vehicle (EV), user behaviour

1 Introduction

The electrification of transport is one of the current megatrends connected with energy transition. The rapidly increasing number of electric vehicles (EVs) will have a widespread impact across multiple sectors. Given renewable primary energy sources, electrification of transport can decrease emissions and thus help in climate change mitigation. However not all impacts are positive, for instance large-scale uncontrolled electric vehicle charging can cause substantial adversities, such as increased peak loads and overload of various grid components. By controlling EV charging, the EV charging load can be, for instance, shifted to night hours, when electricity demand is otherwise low. [1] The shift of charging load can be regarded as demand-side management, or demand response (DR). Demand response aims to manage consumers electricity consumption in order to influence the total load of the electric utility [2].

From customer perspective, the control of EV charging should not interfere with the desired outcome of charging; a charged battery. This poses difficulties to possible demand response operators, as the control of EV charging events should be executed in a way that causes as little inconveniences as possible to the EV owners, and in a way that maximizes the benefits gained from demand response operations. This kind of controlled EV charging is frequently referred to as smart charging [3]. Smart charging is usually used to describe implicit demand response programmes, which encourage consumers to shift their charging demand in order to minimize EV charging cost. As implicit demand response is based on time-variant electricity pricing, it is sometimes referred to as time-based demand response. In contrast to implicit DR, explicit DR loads can participate on different electricity and ancillary service markets, and thus provide extra income to participating parties. Due to possible extra income gained from offering controllable loads to the power system, explicit DR is sometimes referred to as incentive-based DR. [4] Explicit demand response can be used for instance to stabilize the power grid frequency during disturbances.

Especially in private EV charging, the plug-in times of EVs to the Electric Vehicle Charging Equipment (EVSE) are usually longer than the time it takes for the electricity demand of the charging event to be filled. The ratio of the actual charging time of an EV to the plug-in duration of the EV can be seen to denote the demand response potential of the charging event. Another important factor when considering the DR potential of EVs is the idling time, which can be denoted as the plug-in duration minus charging time. Overall, the possibility to interrupt or decrease the power of an EV charging event without decreasing electricity transfer signifies potential for customer-friendly demand response. These interruptible charging events could be identified based on historical data, and for instance a mobile application could be used to ensure that the EV owners can control the charging based on their changing needs.

Analysis of idling time is important due to the possibility of utilizing charging network in demand response schemes, but also due to EV user satisfaction. In private or non-public EVSE the demand response aspect can be seen as more important, but when considering public chargers, the excess idling time should be minimized to maximize the availability of charging stations to other EVs. Excessive idling on public EV chargers has a negative impact on the whole charging infrastructure, as it affects the availability, sizing and cost of the system [5]. Analysis, prediction and measurement of EV idling times is thus important for multiple actors. Idling time estimation has been largely overlooked in previous scientific research, one of the exceptions being [5], where the authors used different machine learning algorithms to predict idling times based on a Dutch EV charging dataset. The identified main factors that impact idling time were intraday hour and total energy supplied during the charging event [5]. According to [6] the main factors that influence the total connection time of EVs to EVSE are time-of-day related factors and the rated power of the EVSE. It can be assumed that these factors (duration, time-of-day, supplied energy & EVSE rated power) are also the main factors when assessing the interruptibility potential of private electric vehicle charging.

2 Methodology

In this study, real-world Finnish private EV charging events are analysed in order to solve the interruptibility potential of private electric vehicle charging. After initial data pre-processing, in which all erroneous, inaccurate and unrelated charging events were removed from the dataset, the final dataset consists of almost 140,000 EV charging events conducted on Finnish private EV chargers between January 2018 and June 2019. These events are studied descriptively to get an understanding of the charging behaviour of private electric vehicle charging. Additionally, as the realized charging powers of the charging events are unknown to the charging point operator, the charging powers have to be evaluated based on multiple assumptions.

As the dataset includes both AC and DC charging stations, the differences between these have to be considered when assessing realized charging powers. For instance, AC charging stations require the use of an on-board charger to convert AC to DC that can stored to the EV battery. Due to weight, space and cost-constraints, these on-board chargers typically set a limit for the maximum power EV's can accept from AC-chargers [7]. For instance, the 2019 model of Nissan Leaf Acenta has a 6.6 kW on-board charger, and thus the maximum charging power from a Mode 3 AC-charger is 6.6 kW [8]. The specifications of the on-board chargers are crucial for assessing the actual charging power of AC charging events as these chargers usually limit the maximum charging power [9]. In contrary to AC-chargers, DC charging stations bypass the on-board charger, and can be assumed to provide full maximum power of the EVSE to the EV battery [10].

As most AC-chargers do not detect the model of the connected EV, the restrictions imposed by on-board chargers are assessed based on fleet averages. Finnish Transport and Communications Agency's statistics of electric vehicle registrations in Finland [11] are used in conjunction with manufacturer information in order to calculate the mean capability of the Finnish EV-fleets on-board chargers. The mean maximum intake power of the current on-board chargers in the Finnish EV-fleet was calculated to be around 5.5 kW in 2019.

The time it takes to transfer the energy charged during a charging event, $t_{charging}$ (1), is solved based on the charged energy, E, and the maximum power intake, P. For DC-chargers the maximum power intake is the power of the charger, whereas the fleet average on-board charger power is used for for AC-chargers.

$$t_{charging} = \frac{E}{P} \tag{1}$$

The actual charging and idling durations are solved based on the assessed charging powers, the plug-in durations and the transferred energies of the charging events. The charging ratio (2) indicates the proportion between charging time, $t_{charging}$, and plug-in time, $t_{plug\text{-}in}$, of the EV charging event.

$$Charging\ ratio = \frac{t_{charging}}{t_{plug-in}} \tag{2}$$

For instance, a ratio of one indicates that the EV is charging the whole plug-in duration. If the ratio is less than one, the event is interruptible, i.e., the event can either be interrupted, or the charging power can be reduced, without sacrificing energy transfer. The potential for charging power reduction can be solved by utilizing information about charging point capabilities.

The idling time, t_{idle} (3), can be calculated by subtracting the charging time, $t_{charging}$, from total plug-in time, $t_{plug\text{-}in}$. Idling time is the time the EV is connected to the charging point but does not charge any energy.

$$t_{idle} = t_{plug-in} - t_{charging} \tag{3}$$

With previous equations, we can solve the interruptibility potential of a single charging event. Interruptibility potential can be defined as the ratio between idling time and plug-in time. This interruptibility ratio (4) thus describes the proportion of total plug-in time the charging could be interrupted without affecting the result of the charging event.

$$Interruptibility\ ratio = \frac{t_{idle}}{t_{plug-in}} \tag{4}$$

Interruptibility ratio of the EV charging network can be assessed through charging ratios, idling times and interruptibility potentials of the dataset. It is for instance possible to generalize the results from this dataset to the whole EV charging network of a region, and thus assess the interruptibility potential.

3 Results

Prediction of EV plug-in moments is one essential aspect when considering the utilization of EVs as demand response. EV charging events are usually started when the driver arrives to a certain destination e.g. home or workplace. The plug-in distributions differ between public and private charging stations, as for instance people tend to arrive home and plug-in their EVs in quite a cyclical manner. The distribution of plug-in moments of the assessed dataset is presented in Figure 1. The mean and median arrival times are around 1 p.m., but the peak plug-in moment is around 8 a.m. This peak can be regarded to result from charging events conducted on private workplace charging stations.

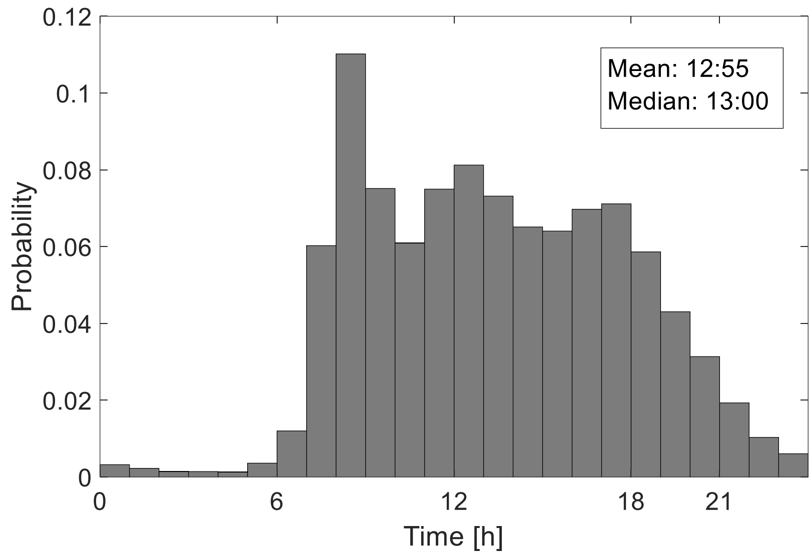

Figure 1: Distribution of charging event plug-in moments

The EV charging powers were assessed as described in section 2. The distribution of charging powers is presented in Figure 2. In the dataset over 80% of the charging events were conducted on AC-chargers, and only around 20% on fast DC-chargers. This is apparent also from Figure 2, where it can be seen that most charging events were conducted with 5.5 kW, the calculated average power of Finnish EV fleets on-board chargers. The results are quite rational as most non-public EVSE are AC-chargers, where the EV on-board charger specification tends to act as a restriction for realized charging power.

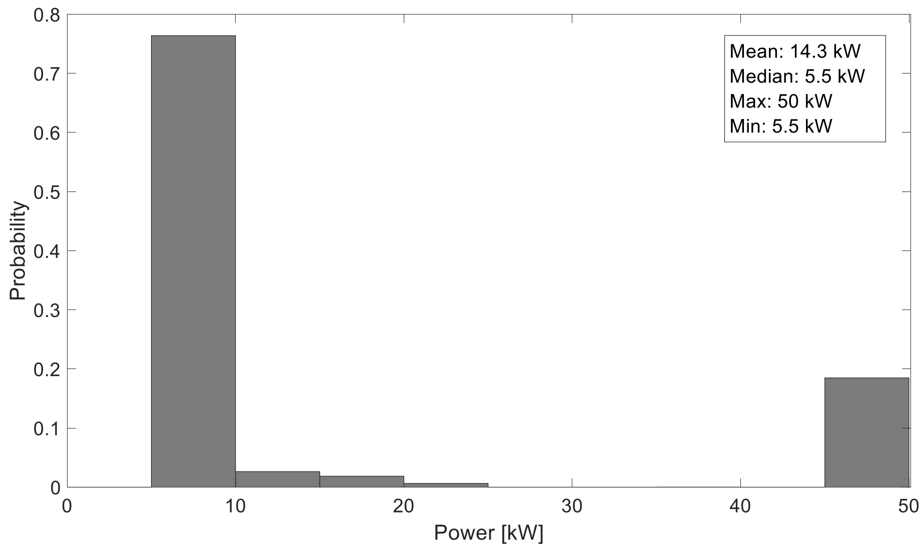

Figure 2: Distribution of estimated charging powers

Idling durations of charging events were assessed based on the estimated charging powers, realized plug-in durations, and charged energies. The probability density functions (PDF) of EV plug-in and idling times are presented in Figure 3. The average idling time is close to 3 hours, and thus over 72% of the average duration EVs are connected to the EVSE. The average time an EV is actually charging is around 65 minutes, implying that on average an EV spends over two and a half times longer idling than actually charging.

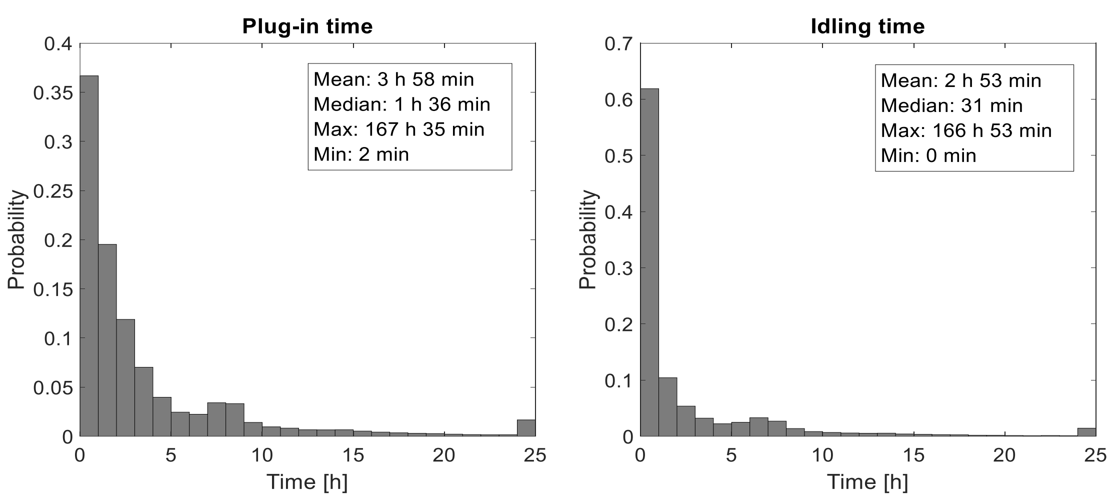

Figure 3: Plug-in & Idling time PDFs (1 hour bin width, last bin contains all values until max value)

Figure 4 exhibits the probability density function (PDF) and the cumulative density functions (CDF) of assessed charging ratios. Based on the cumulative distribution function, over 70% of charging events are interruptible. That is, the majority of charging events can be interrupted if needed without sacrificing the charging energy transfer. Roughly 70% of the events can be interrupted for at least 10% of the time they are plugged-in, that is the charging ratio is smaller than 0.9. The average ratio between charging time and plug-in duration is around 0.58 with median being 0.59.

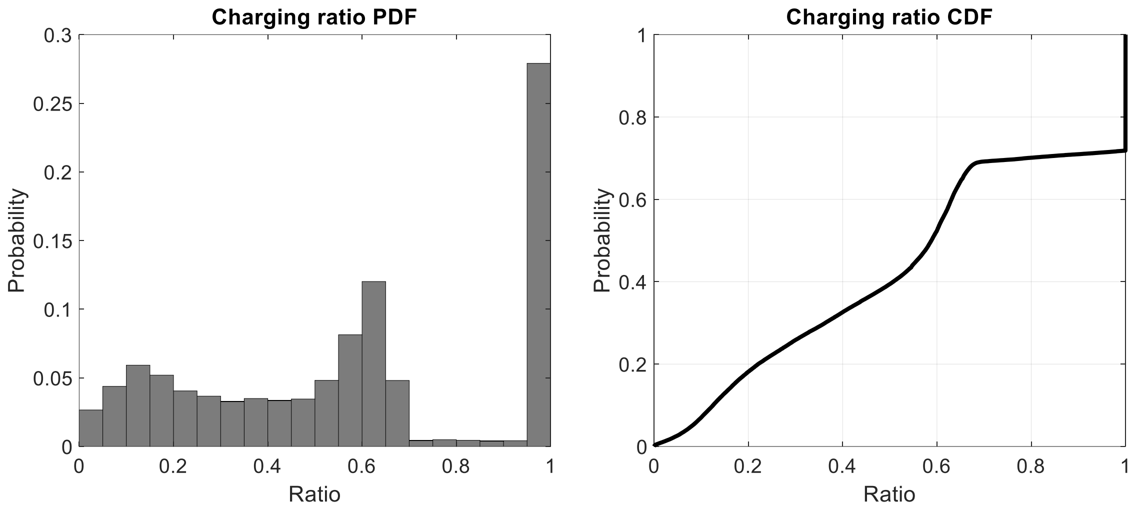

Figure 4: Charging ratio PDF and CDF

Another way to illustrate the possibility of charging event interruptibility is by the interruptibility ratio introduced in the previous section. If this interruptibility ratio is larger than zero, the charging event can be interrupted without sacrificing energy transfer. Interruptibility ratios of the assessed dataset are presented in figure 5. It should be noted that only around 30% of charging events had an interruptibility ratio of zero, meaning the EV spent the entire plug-in duration charging. The average interruptibility ratio is around 0.42 with median being 0.41, implying that over 40% of total plug-in time is spend idling in an average charging event.

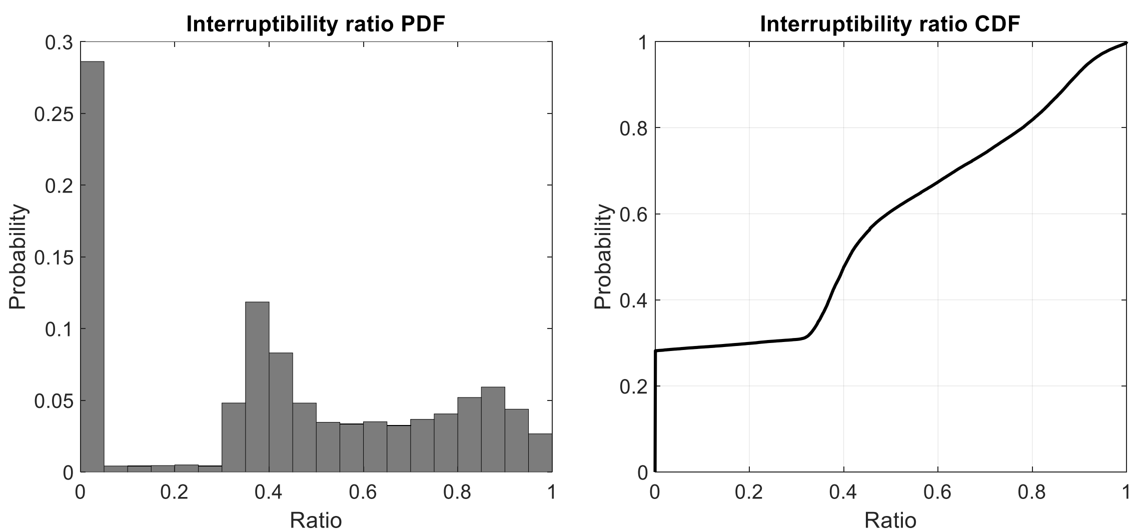

Figure 5: Interruptibility ratio PDF and CDF

Figure 6 exhibits the hourly distribution of average interruptibility ratios. It can be noted that in morning between 6 a.m. and 9 a.m. the EVs spend majority of plug-in duration idling. This implies that charging interruptions can take over half of the plug-in time of the EV without affecting the charging of the EV. On charging events started between 7 a.m. and 8 a.m., the average interruptibility ratio is over 64% of the total plug-in time. This means, that the 64% of the duration of the charging event can be used to provide, for instance, demand response or load balancing.

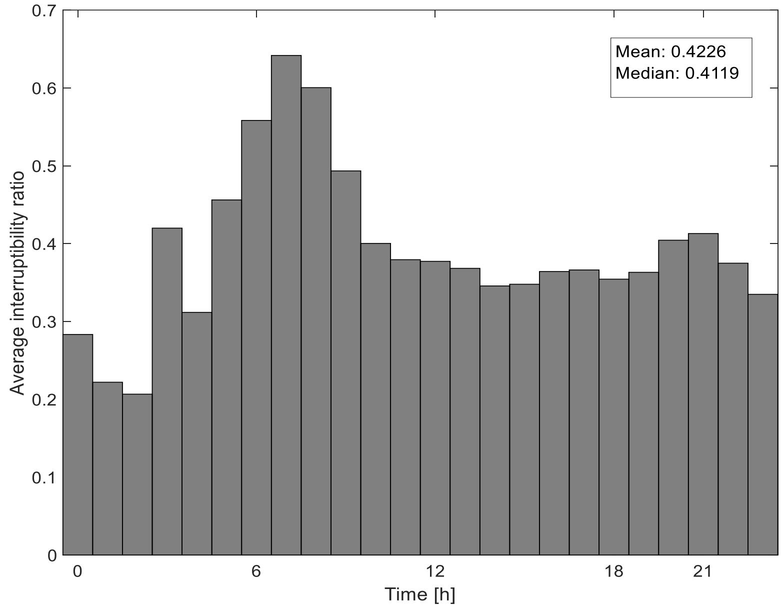

Figure 6: Hourly distribution of average interruptibility ratios

4 Discussion

Based on the results of this study, the majority of Finnish private EV charging events are interruptible and can be utilized in different demand response schemes. Roughly 70% of the events can be interrupted for at least 10% of the time they are plugged-in to the EVSE. The calculated interruptibility ratio is around 0.42 with median being 0.41. This implies that the interruption, or the decrease of charging power, is possible in a major part of private EV charging events without discomfort to customers. Short interruptions of EV charging events could be beneficial especially during short-term grid disturbances on local, distribution and transmission system levels.

The results gained in this study differ somewhat from previous studies done conducted with public EVSE data. In [12] based on analysis of EV charging events conducted in the Netherlands during 2014 and 2015, the authors found that the idle time was on average 64.1% of the total connection time. In [5], with a larger Dutch public EVSE dataset, the mean idle time was 62.3% of connection time. The differences could be caused for instance by regional differences and by different utilization patterns between public and private charging stations. For instance, according to [6] plug-in durations to public level 2 AC-chargers are highly associated with parking preferences as people tend to use these EVSE as parking spaces.

The interruptibility potential of EV charging can be seen as a great opportunity for power grid balancing. As the number of electric vehicles and smart electric vehicle charging stations increase, the aggregated interruptibility potential translates into a formidable demand response load. Future research of the authors will concentrate on the assessment of the EV charging demand response potential and on simulation in order to estimate future potential. Overall, the utilization of EV idling time offers the possibility to conduct load scheduling, power reduction and load shifting without affecting the desired output of the charging event, a charged EV.

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