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Pinpointing the Smart Charging Potential for Electric Vehicles at Public Charging Points

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Executive Summary

The peaks in electricity demand for charging electric vehicles (EVs) correspond with the peaks of household electricity demand. As the number of EVs will increase, the demand for electricity at these peak moments will increase even further. Research on public charging infrastructure, shows that the charging time of EV's (the time EV's are connected and charging) is on average 20% of the total connection time. This suggests a high potential for smart charging which can be unlocked by e.g. rescheduling the charging sessions optimizing for the grid while meeting the demand of EVs at the same time.

The focus of this research is to develop a methodology to assess the potential for smart charging and suggest possible smart charging strategies. Based on the start time of a charging session and the total connection time three main user categories are defined for which the smart charting potential is determined. Based on this research, we can conclude that approximately 40% of all charging sessions start between 16:00 and 20:00, a category that has a smart charging Potential of 75% or higher.

Keywords: charging, energy consumption, modeling, smart charging, user behaviour

1. Introduction

Adoption of electric vehicles (EVs) will have a direct impact on the electricity grids via additional demands at current peak hours. For the Netherlands, previous studies have shown that an instant replacement of the current car fleet (non-EVs) by EVs given the current mobility pattern will lead to an increase of 23% in the total annual electricity demand. Furthermore, the peak load will even rise by up to 43% [1]. The majority of this demand will occur via the low-voltage grid connections (i.e. public and private charging points). The low-voltage grid has its limitations in terms of power flows and its capacity. In some areas it will not be able to cope with the additional demand by EVs which will most probably happen at the current and existing peak times on the grid. smart charging of EVs offers an alternative for better managing and incorporating the additional electricity demand of EVs within the existing power system. Smart charging can be defined as follows; optimizing the charging session by alignment of (i) time, (ii) speed, (iii) direction, and (iv) charging method with the EV-user's preferences, given electricity market and grid conditions.

The concept of smart charging has been tested in several contexts and pilots [2]. Results from most recent experimental projects confirm that controlled charging of EVs can work in practice both at public and home charging stations. Regarding smart charging at public chargers; the outcomes of a pilot project which took place in Amsterdam (FlexPower) show that on average charging rate of EVs was increased by 45% (from 4.05 kW to 5.86 kW) outside peak hours while reducing the charging power during the peak moments [3].

The results from FlexPower project are mainly applicable to the situation of Amsterdam. The main objective of this research is to provide insights in the smart charging potential (SCP) of EVs at public charging points.

In the Netherlands the majority of electric vehicles are Battery Electric Vehicles (BEVs) and Plugin-Hybrids (PHEVs) as can be seen in figure 1. Although the PHEVs are dominating the market, the number of BEVs has more than doubled in 2018. Although the EV sales are rapidly increasing in the Netherlands, a small 2% of passenger vehicles are EVs. The ambition of the Dutch government is to increase the number of EVs up to 2 million by 2030 [4]. Assuming that the current charging behaviour will be adopted by 2 million EVs, the electricity grid will not be able to cope with such power demand in many areas. Therefore, demand side management solutions such as smart charging will be needed.

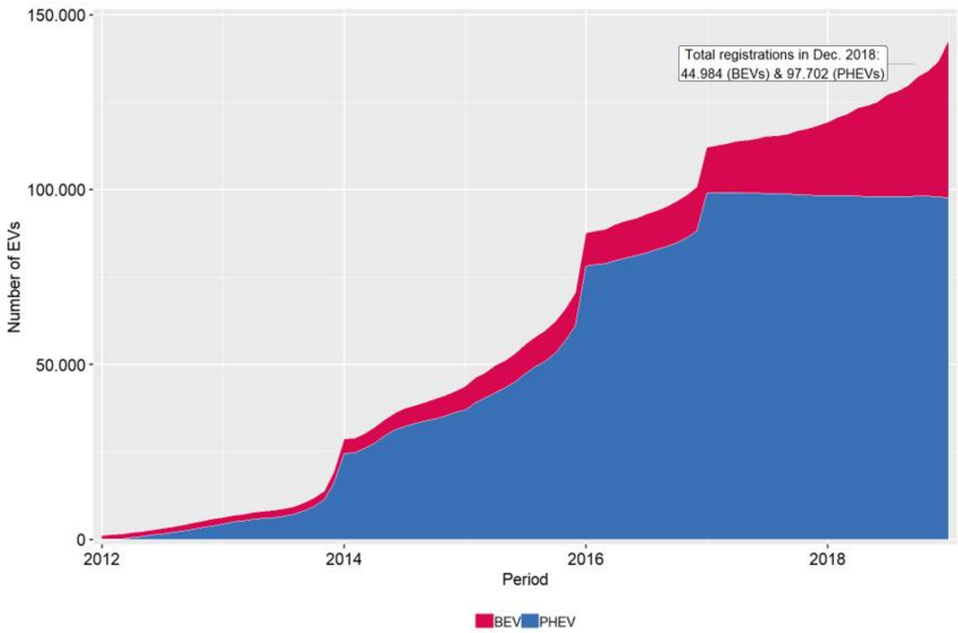


Figure 1. The number of EVs in the Netherlands.
This figure is based on data from The Netherlands Enterprise Agency (www.rvo.nl).

In order to successfully apply smart charging, an understanding of its potential is necessary. In this study a methodology is proposed to assess the SCP of EVs.

2. Data and Methodology

This section includes background information regarding the input datasets and elaboration on the several dimensions that we have looked at in order to quantify the smart charging potential.

2.1 Dataset structure

In this research we have analysed one of the largest databases of charging sessions on public charging infrastructure available worldwide. The dataset covers a significant part of the Netherlands and contains data on both rural and urban areas. The dataset used for this research consists of two major datasets. First the EVnetNL charging data, with charging sessions from nationwide network of charging points. Second the G4 / MRA-Electric[1] (MRA-E) data from urban areas including the four large cities of Amsterdam, The Hague, Rotterdam and Utrecht and the Metropolitan Region of Rotterdam (MRR[2]). For this study, data from the years 2015 and 2016 is used. In those years, the EVnetNL dataset contained 605.440 charging sessions by 33.907 unique RFIDs at 1.538 charging stations. The G4 / MRA-E dataset contained 2.177.351 charging sessions by 56.988 unique RFIDs at 4.428 charging stations. An summary of the data is shown in table 1.

Dataset	Regions	Charging sessions	Unique RFIDs	Charging stations
EVnetNL	Noord Brabant Gelderland Other	605.440	33.907	1.538
G4 / MRA-E	Amsterdam Den Haag Rotterdam Utrecht MRA-E MRR	2.177.351	56.988	4.428

Table 1. Summary of data used in this research. The data contains two dataset spanning different regions in the Netherlands.

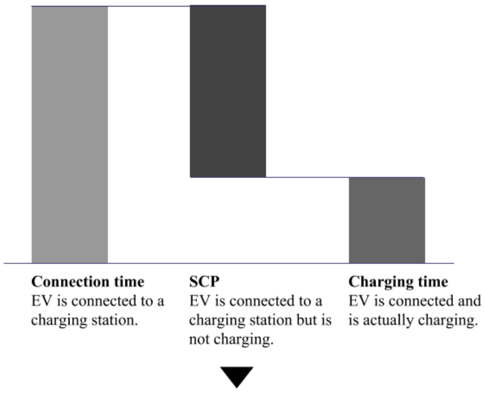
The dataset used in this research contains charging sessions with a connection duration up until 24 hours. Although in reality there are charging sessions that have a longer connection duration, these sessions are rare and considered to be outliers..

2.1 Methods

Based on the historical charging events the charging behaviour is explored to quantify the SCP. The SCP is defined by the ratio of charging time and connection time. Connection time is the duration whereby an EV is connected to a charging point. Charging time is the portion of connection time where active energy transfer is taking place. Figure 2 includes a schematic decomposition of connection time into charging time, and SCP. So, SCP here is a measure of flexibility to postpone a charging event.

[1] MRA-E includes of the provinces of Noord Holland, Flevoland and Utrecht and excludes the city of Amsterdam.

[2] MRR includes Albrandswaard, Barendrecht, Brielle, Capelle aan den IJssel, Delft, Gouda, Hellevoetsluis, Kaag en Braassem, Krimpen aan den IJssel, Lansingerland, Leidschendam-Voorburg, Maassluis, Midden Delfland, Nissewaard, Pijnacker-Nootdorp, Ridderkerk, Rotterdam, Schiedam, Vlaardingen, Voorschoten, Wassenaar, Westland and Westvoorne.



$$SCP = \frac{Connection\ time - Charging\ time}{Connection\ time} \cdot 100$$

Figure 2. Schematic definition of smart charging potential

In this study the definition SCP as shown in figure 2 is explored in various dimensions. First a distinction is made between the different user types and their SCP. The data used for this study contains charging sessions of regular users, charging sessions of taxis and car sharing schemes. The second dimension considered in this study is the EV type. For this dimension a distinction is made between BEVs and PHEVs. The third dimension considered in this study is the level of urbanity. Statistics Netherlands (CBS) categorizes regions in one of five levels of urbanity based on the number of home addresses per square kilometre. Level 1, the *highest* level of urbanity, is attributed to regions with more than 2.500 addresses per square kilometre. Level 5, the *lowest* level of urbanity, is attributed to regions with less than 500 addresses per square kilometre.

2.1.1 Charging sessions for different user type

The dataset used in this study contains four main categories of EV users: regular users, taxis, car sharing schemes and electric buses used in public transport. The number of sessions for each user type is shown in table 2. A small percentage of charging sessions (4.8% and 2.4% for G4 / MRA-E and EVnetNL respectively) cannot be attributed to a specific user type due to lack of information. As can be seen in table 2, the two datasets show differences in the share of taxis and car sharing schemes. These two user categories are mainly present in urban areas which are part of the G4 / MRA-E dataset.

As can be seen in table 2 regular users contribute to the majority of charging sessions (95.8% and 99.9% for G4 / MRA-E and for EVnetNL respectively). Due to the relatively small contribution of other users, a comparison of the SCP for the different user types is not looked into further in this study.

G4 / MRA-E

User type	Sessions	Percentage
Regular	1991431	95.8%
Taxi	68835	3.3%
Car sharing	17455	0.8%
Public transport	229	0.0%
Unknown	99401	4.8%
Total	**2177351**	**100%**

User type	Sessions	Percentage
Regular	591657	99.9%
Taxi	350	0.1%
Car sharing	30	0.0%
Public transport	0	0.0%
Unknown	13403	2.3%
Total	**605440**	**100%**

Table 2. The number of charging sessions for the different user types for both datasets.

2.1.2 Charging sessions for BEVs and PHEVs

The dataset used for this study does not contain information about the vehicle type. In order to have insight in the SCP for BEVs and PHEVs, a vehicle type label must be attributed to each RFID.

Labelling can be done in different ways. Here it is chosen to label the vehicle type based on a simple classification using charging speed and battery capacity. From the historical data, the charging speed and battery capacity are estimated. Based on these estimates the classification of RFIDs in either BEV of PHEV is determined using the methodology outlined in [5]. A simplified version of classifying EV types is shown in figure 3. The underlying assumption is twofold. First based on available PHEV models on the market in 2016 it can be assumed that PHEVs have a battery capacity less than 16 kWh. Second it is assumed that the charging speed of PHEVs is lower than 3.8 kW. These assumptions are based on EV data[3]. There are PHEVs available that have more battery capacity than 16 kWh and a charging speed higher than 3.8 kW (e.g Audi Q7 E-Tron). These PHEV models where launched starting from 2016. Similarly there are BEVs that have an onboard charger that limits charging to 3,7 kW. By taking at least 10 sessions per RFID we are assuming that at least one of these charging sessions was started with a low state of charge, requiring more than 16 kWh capacity (given that most BEVs have battery packs of >16 kWh). These assumptions provide a fairly good distinction between PHEVs and BEVs given that the dataset used in this research is from the years 2015 and 2016.

		Battery capacity	
		> 16 kWh	**< 16 kWh**
Charging speed	**> 3.8 kW**	BEV	BEV
	< 3.8 kW	BEV	PHEV

Figure 3. Classification of RFIDs in BEVs and PHEVs
based on charging speed and battery capacity

G4 / MRA-E

EV type	Sessions	Percentage
BEV	493914	22.7%
PHEV	1683367	77.3%
Unknown[4]	70	0.0%
Total	**2177351**	**100%**

EVnetNL

EV type	Sessions	Percentage
BEV	205689	34.0%
PHEV	399724	66.0%
Unknown	27	0.0%
Total	**605440**	**100%**

Table 3. Characterisation of EV type based on charging speed and battery capacity.

As can be seen in table 3, PHEVs contribute to the majority of charging sessions (77.3% and 66.0% for G4 / MRA-E and EVnetNL respectively. In the results section the difference in SCP for these two EV types will be looked into.

[3] Data from: https://www.elektrischeauto.nl/overzicht/accucapaciteit/plug-in-hybride/

[4] Some charging sessions could not be characterized due unrealistic values of negative charging speeds and negative battery capacity.

2.1.3 Charging sessions for different urbanity levels

To characterise the different regions where the charging sessions took place the level of urbanity is used as defined by the CBS[5]. The CBS distinguishes five levels of urbanity with 1 for *high* urbanity and 5 for *low* urbanity levels. The level of urbanity is defined based on the number of addresses per square kilometre. See table 4.

Level	**5**	**4**	**3**	**2**	**1**
Description	Very low urbanity	Low urbanity	Medium urbanity	High urbanity	Very high urbanity
Number of addresses per km^2	< 500	500 - 1000	1000 - 15000	1500 - 2500	> 2500

Tabel 4. The level of urbanity defined by Statistics Netherlands (www.cbs.nl)

Based on this definition of the level of urbanity, the charging sessions are characterised as shown in table 5 and 6. For each region in the datasets the percentage of charging sessions that took place in areas with certain level or urbanity is shown. The number of sessions per region, per level of urbanity can be computed by simply multiplying the total number of sessions in each dataset by the percentages shown in tables 5 and 6.

As can be seen in these tables, the G4 / MRA-E datasets covers mainly areas with high level of urbanity while the majority of the sessions in the EVnetNL dataset took place in areas with medium and low levels of urbanity.

G4 / MRA-E (Total sessions = 2177281)

	5	**4**	**3**	**2**	**1**	**Total**
Amsterdam	0.0%	0.0%	0.3%	2.5%	25.4%	28.3%
Den Haag	0.0%	0.0%	1.4%	1.8%	9.1%	12.3%
MRA-E	1.8%	4.2%	5.7%	11.1%	6.0%	28.7%
MRR	0.1%	0.5%	1.5%	3.1%	1.4%	6.5%
Rotterdam	0.1%	0.5%	1.2%	3.0%	10.3%	15.1%
Utrecht	0.0%	0.0%	1.3%	1.4%	6.4%	9.1%
Total	2.0%	5.1%	11.4%	22.9%	58.5%	100.0%

Table 5. The distribution of charging sessions per region and urbanity level in the G4 / MRA-E dataset.

[5] Definition given by the Statistics Netherlands (www.csb.nl) for the Level of urbanity.

EVnetNL (Total sessions = 605413)

	5	4	3	2	1	Total
Gelderland	2.0%	6.7%	6.2%	9.3%	3.8%	28.1%
Noord Brabant	2.4%	6.1%	8.4%	11.1%	18.1%	46.0%
Other	3.3%	3.3%	4.3%	8.7%	6.4%	25.9%
Total	7.7%	16.1%	18.9%	29.0%	28.3%	100.0%

Table 6. The distribution of charging sessions per region and urbanity level in the EVnetNL dataset.

2.1.4 Charging sessions distribution using heatmaps

In order to better understand the SCP it is chosen to characterize the charging behaviour of EV drivers based on the time at which (i) a connection starts and (ii) the connection duration. For these two dimensions the distributions of the charging sessions is plotted as an indication of the distributions of the charging demand. This is shown in figure 4. The colour in the heatmap is an indication of the distribution of the number of charging session with red for high and blue for low intensity.

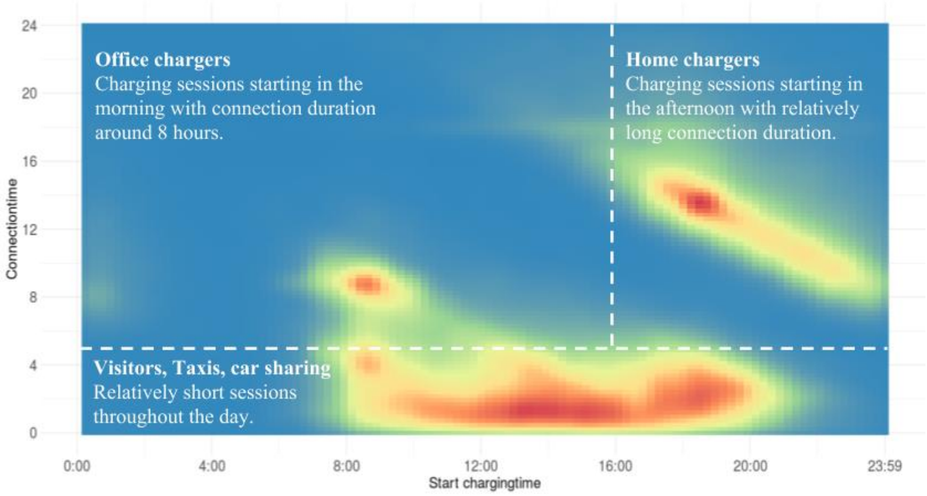


Figure 4. User categories based on start and duration of session

What is interesting in using heatmaps as shown in figure 4, is the ability to see how the charging sessions are distributed. For example, three main clusters of charging sessions can be distinguished. Charging sessions of (i) office chargers, (ii) home chargers and (iii) a cluster that contains different user type with relatively short sessions through the day (labelled as visitors).

So, in order to see how the SCP is distributed, similar heatmaps will be used in the next section. A major difference between the heatmap shown in figure 4 and the heatmaps that are shown in the results section is that on the y-axis the SCP is shown instead of connection duration. In this way one can see at each start time of charging sessions what the SCP distribution is.

3. Results

In this section the results of the study will be discussed based on the data and methodology description given in the previous section. Due to the size of the dataset (more than 2.7M transactions) and its heterogeneity we believe that these outcomes provide a representative view of the current EV charging behaviour and the possibilities for smart charging in the Netherlands.

3.1 Clusters of charging sessions

First, the three cluster of charging sessions (see figure 4) are defined based on the starting time of a charging session (horizontal axis) and the connection time (vertical axis). In figure 4 the cluster of the morning charging sessions can be seen. The sessions in this cluster start on average around 8:00 and have on average a connection duration of 8 hours. This cluster is labelled as office chargers.

The cluster of evening sessions on the other hand contains sessions that start in the evening and remain active throughout the night. The most charging sessions in this cluster start around 18:00 with an average connection duration of 13 hours. As time progresses the connection duration of the charging sessions in the evening cluster decrease due to decreasing number of hours remaining till the next day. This is reflected in the downward slope of this cluster. This cluster is labelled as home chargers.

The final cluster than can be seen in figure 4 is labelled as visitors. The sessions in this cluster can start at any moment in the day and have a relatively shorter connection duration. This cluster is more complex than the other two cluster since it contains sessions from different user categories with different behaviour characteristics.

The identification of these two clusters makes it possible to relate the distribution of SCP as discussed in the next sections to the clusters shown in figure 4.

3.2 Smart charging potential per EV type

Figures 5 and 6 show the distribution of charging sessions for BEVs and PHEVs given the start time of a charging session and SCP. Figure 5 shows the results for Amsterdam in the G4 / MRA-E data while figure 6 show the results for Gelderland in the EVnetNL dataset. In these figures it is chosen to show two dissimilar regions with Amsterdam as a highly urban and Gelderland as a rural area.

From the results in figures 5 and 6 one can conclude that in most cases, the sessions with high SCP start in early evening and late afternoon. In general around 40% of the sessions start between 16:00 and 20:00 and have an SCP of 75% or higher. Sessions starting at these times are mainly sessions that take place throughout the night which implies that the portion of the connection time that an EV is connected but not charging is relatively higher. Hence the relatively high SCP.

Second, it can be seen that in general the portion of PHEVs with an SCP higher than 75% is higher than the portion of BEVs in the same SCP range. In general PHEVs have a lower battery capacity which means that the time to charge a BEV is in general longer. This implies that a similar charging session (e.g. a home charger) with a PHEV has a higher SPC since the portion of the connection time that an PHEV is not charging while connected to a charging point is larger.

Third, comparing the distribution of the SCP between the BEVs and PHEVs it can be seen that the distribution of SCP for PHEVs is more concentrated around a starting time from 16:00 to 20:00. For BEVs however the distribution is less concentrated around specific connection times. As we see in figure 5, in Amsterdam, the number of charging sessions with a SCP higher than 75% is 5% lower for BEVs compared with PHEVs.

Fourth, for Gelderland (figure 6) the distribution of SCP for PHEVs shows a similar pattern as in Amsterdam (figure 5) while the distribution of SCP for BEVs the very different. In this distribution three different regions of concentration can be observed. In addition to the peak between 16:00 and 20:00, there is a peak in the morning with high SCP and a concentration of sessions with SCP around 25% throughout the day. This means that for Gelderland, the morning sessions have high SCP in addition to the evening sessions. These insight can be used as input for defining optimal smart charging strategies. For example, the application of smart charging for the morning sessions might focus on solar charging while smart charging for the evening sessions might be focused on utilizing wind energy.

From the results shown in figures 5 and 6 one can conclude that charging sessions with high SCP are sessions that starting between 16:00 - 20:00. In addition, these sessions account for more than 40% of the total number of sessions, so the impact of applying SC to these sessions would be relatively high.

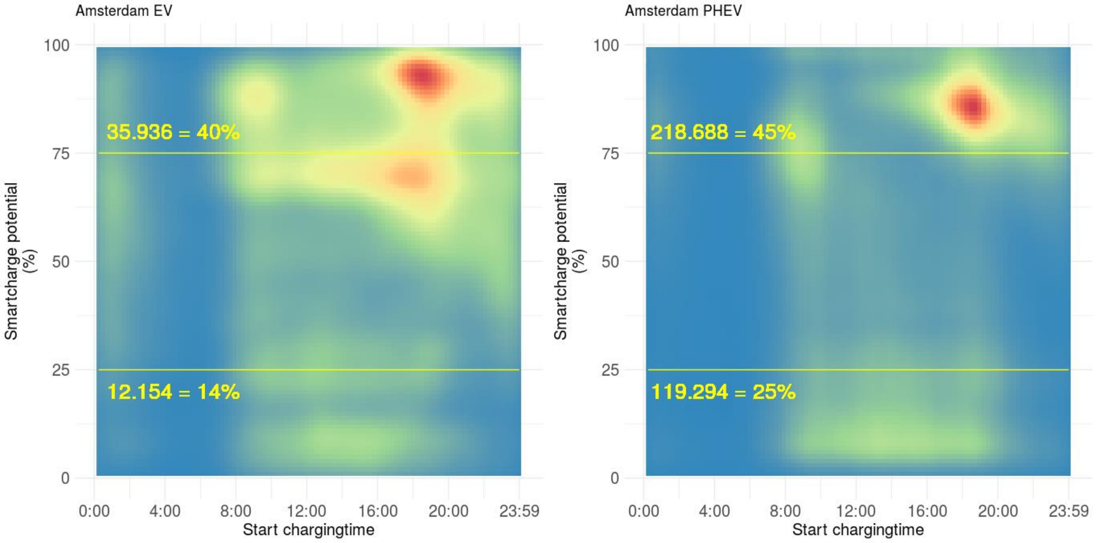


Figure 5. The distribution of the SCP for BEVs and PHEVs in Amsterdam in the G4 / MRA-E dataset.

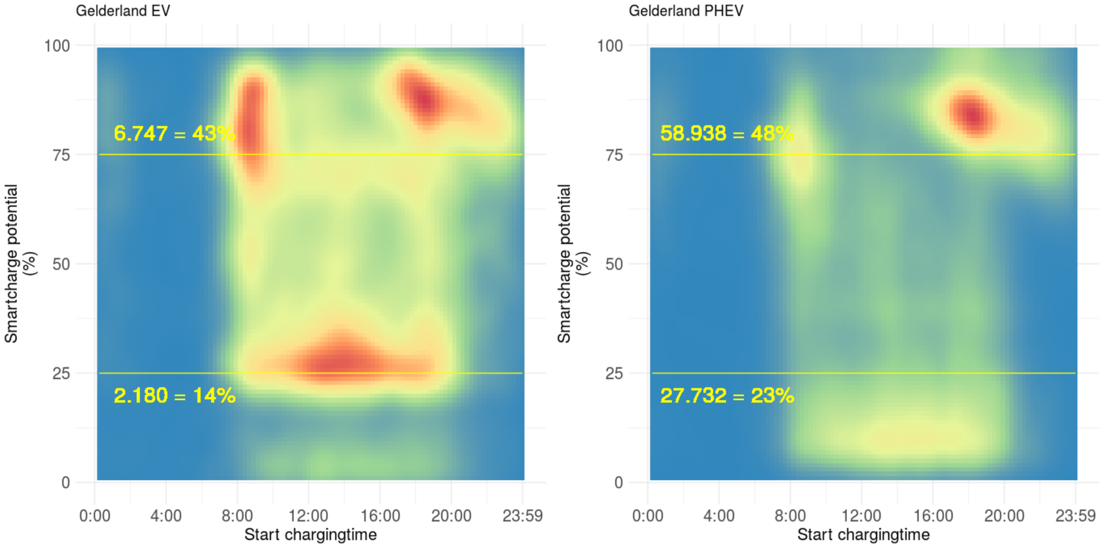


Figure 6.The distribution of the SCP for BEVs and PHEVs in Gelderland in the EVnetNL dataset.

3.3 Smart charging potential per geographical location characteristics

The SCP per geographical location characteristic is analysed using the level of urbanity as defined by CBS. The distribution of SCP for the lowest and highest levels of urbanity is shown in figure 7 for the G4 / MRA-E dataset and in figure 8 for the EVnetNL dataset.

In figures 7 and 8 the same general pattern is observed with the majority of charging sessions starting between 16:00 and 20:00 having an SCP of 75% and higher. Furthermore, we can observe in both figures that as the level of urbanity decreases the distribution of SCP becomes less concentrated around these specific connection times. Due to the definition of level of urbanity based on the number of addresses per square kilometre, it is expected that regions with high levels of urbanity have more residential addresses than regions with low levels of urbanity. This implies that in regions of high urbanity EVs will be charging at home. And as can be seen in figure 4 these sessions take place in the evening and hence the higher SCP for evening sessions. Regions with lower levels of urbanity are expected to have less residential addresses. This implies that part of the charging sessions in these regions will occur during the day and will have a lower SCP than the home charging sessions since the average connection duration of charging session through the day is generally lower (see figure 4). The lower connection duration leads in this case to lower SCP as can be seen in figures 7 and 8.

From figures 7 and 8 it can be concluded that as the level of urbanity decreases, the distribution of the charging sessions moves from a concentrated distribution of sessions starting between 16:00 and 20:00 to a distribution with sessions throughout the day with lower SCP.

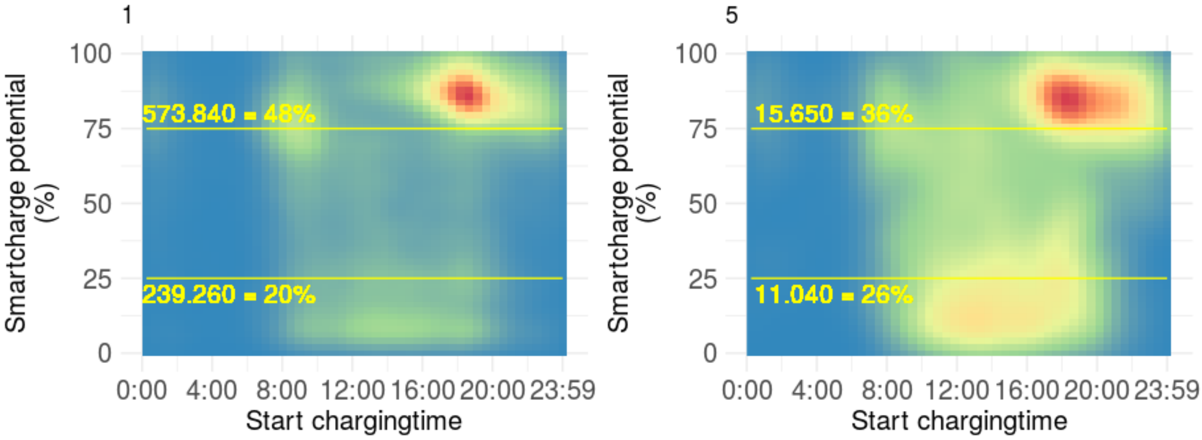


Figure 7. The distribution of the SCP for the highest and lowest levels of urbanity in the G4 / MRA-E dataset.

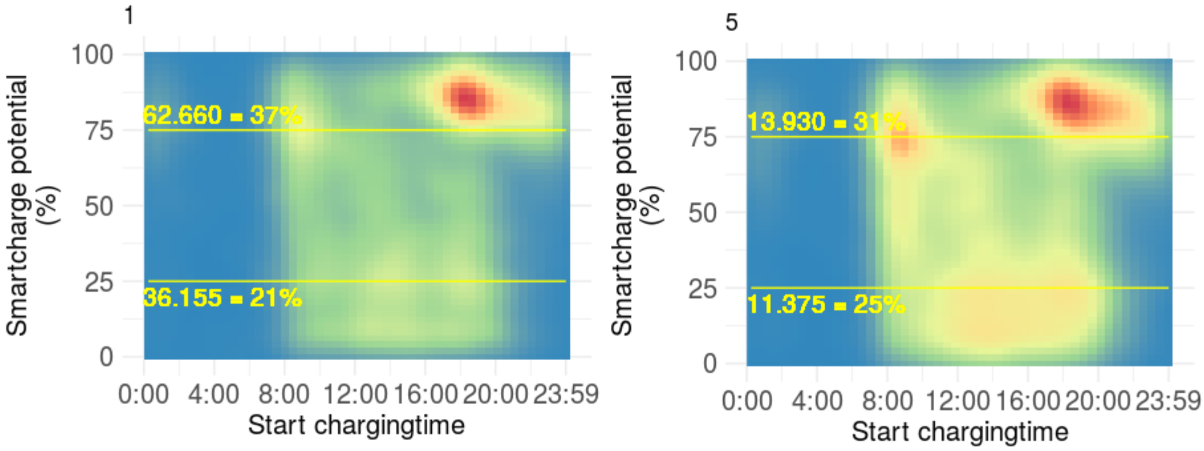


Figure 8. The distribution of the SCP for the highest and lowest levels of urbanity in the EVnetNL dataset.

4. Conclusions and recommendations

In this study we proposed a methodology to assess the SCP of EVs based on charging sessions at public charging points in the Netherlands. The dataset consists of two major datasets: G4 / MRA-E with charging sessions mainly from urban areas and EVnetNL with charging sessions from nationwide network of charging points.

First, the distribution of charging sessions is studied by using heatmaps based on start time and connection duration of sessions. Using these heatmaps (figure 4) three main clusters are identified which are labelled as home chargers, office chargers and visitors. This categorisation of charging sessions allows us to relate the distribution of SCP to specific clusters.

Second, the SCP is quantified using similar heatmaps. The distribution of the SCP for different EV types at different regions is compared. As can be seen in figures 5 and 6 about 40% of the sessions start between 16:00 - 20:00 and have an SCP of 75% and higher. Comparing a highly urban area (Amsterdam) with a rural area (Gelderland) shows that in addition to the high SCP for home chargers, the office chargers in Gelderland have a high SCP too.

In addition to comparing SCP for different EV types, the SCP is compared for different urbanity levels (figure 7 and 8). As the level or urbanity increases, the distribution of the SCP becomes less concentrated around 16:00 - 20:00. This can be explained due to the fact that regions of high levels of urbanity have more residential areas with more home chargers that mainly charge in the evening (figure 4).

Policy makers and market parties (i.e. charge point operators and e-mobility service providers) should assess the possibilities for implementing smart charging services in order to make EVs more beneficial for users. This study proves that there is sufficient potential for e.g. postponing charging sessions without creating any practical obstacles for EV users.

The methodology used in this study might help to pinpoint the smart charging potential which in turn will help policy makers to apply smart charging strategies at the appropriate moment with the appropriate objective. For example, the comparison between Amsterdam and Gelderland shows that Gelderland has the potential to utilize solar power for office chargers and that both Amsterdam and Gelderland can utilize wind power for home chargers.

One should be aware that developments regarding EV characteristics (battery capacity, charging speed etc) are relevant indicators when it comes to SCP. Also, adoption of EVs by wider group of EV users will have implications on smart charging possibilities of EVs. For example, the annual commute distance of average car users is less than the commute distance of the current EV owners. Furthermore, this analysis is done on aggregated level, more research is needed to validate these outcomes at individual level.

References

[1] Beltramo, A., Julea, A., Refa, N., Drossinos, Y., Thiel, C., Quoilin, S. (2017): *Using electric vehicles as flexible resource in power systems: A case study in the Netherlands*. 2017 14th International Conference on the European Energy Market (EEM), Dresden, Germany.

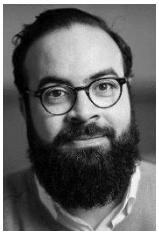
[2] Tamis, M., Van den Hoed, R., and Thorsdottir, H. (2017), *Smart Charging in the Netherlands.* European Battery, Hybrid & Electric Fuel Cell Electric Vehicle Congress Geneva, 14-16 March 2017.

[3] ASC (2018), *Mass-charging electric vehicles by using flexible charging speeds.* Amsterdam Smart City. URL accessed on 2019-03-01: https://amsterdamsmartcity.com/projects/flexpower-amsterdam

[4] Nationale Agenda Laadinfrastructuur. URL accessed on 2019-02-06; https://www.klimaatakkoord.nl/binaries/klimaatakkoord/documenten/publicaties/2019/01/08/achtergrondnotitie-mobiliteit-laadinfrastructuur/Mobiliteit+-+achtergrondnotitie+Nationale+Agenda+Laadinfrastructuur.pdf

[5] Van den Hoed, R., Helmus, H., and Kooij, M. (2016). *Laadgedrag van PlugIn Hybride Elektrische Voertuigen op publieke laadpunten in de G4 en MRA-E.* 2016.

Authors



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Nazir Refa received his Master of Science degree in 2015 from Utrecht University, Netherlands. Currently, he is working as a data scientist at ElaadNL. His primarily research interests are in the field of EV grid impact, and smart charging studies. Within ElaadNL He is contributing to monitoring, and analysis of various smart charging pilots in collaboration with Dutch grid operators. He has co-developed several models for EV adoption, and deployment of EV charging infrastructure.

Robert van den Hoed is Professor Energy and Innovation at the Amsterdam University of Applied Sciences (AUAS), part of the Urban Technology research program. Research topics include electric mobility, optimization of charging infrastructures and smart grids. Van den Hoed is board member of Dutch-INCERT and steering group member of Amsterdam Smart City and National Knowledge platform Charge Infrastructure (NKL).