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Impact of Smart Charging on EVs Charging Behaviour Assessed from Real Charging Events

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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. Smart charging offers an alternative for avoiding these additional peak demands. Jedlix provides a smart charging service via an smartphone application whereby EV-owners allow Jedlix to charge their vehicles at 'beneficial' moments on the grid whereby there is abundance of renewable energy, and electricity prices are relatively low. ElaadNL has analysed a subset of Jedlix charging data from the period October 2017 – June 2018. This study provides novel insights regarding smart charging of EVs based on real data.

Keywords: smart charging, user behaviour, energy consumption, state of charge, business model

1 Introduction

In 2018 the Dutch electric vehicle (EV) sales tripled compared to 2017. In total about 24,000 new EVs were sold. At the same time the share of EVs in total passenger vehicle sales increased to 6.5% [1]. Still, a small fraction of the Dutch vehicle fleet has been electrified yet but country's ambition is to have about 2 million EVs on the road by 2030 [2].

Adoption of electric vehicles (EVs) will have a direct impact on the electricity grids mainly due to additional power demand during current peak hours on the grid. For the Netherlands, previous studies have shown that an instant replacement of the current car fleet (non-EVs) by EVs and given the current mobility pattern will result to an increase of 23% in the total annual electricity demand. Furthermore, the peak load will even rise by up to 43% [3]. Majority of this demand will happen via the low-voltage (LV) grid connections (i.e. public and private charging points). Currently, in the national Climate Agreement the target is to increase the number of chargers up to 1.9 million in 2030 [2]. However, the LV has its limitations in terms of power flows and its capacity.

A typical Dutch household has 3*25 Ampere (A) connection. So, in theory this connection type could deliver up to 17.3 kW but the current LV grid is built for a maximum capacity of 4 kW, and on average an household has an actual peak power demand of about 0.8 kW [4]. Recent studies have shown that EVs could increase this average peak demand between 1 – 2.8 kW depending on EV type [5]. So, it means that actual peak demand could potential more than threefold in the future. Higher adoption of EVs will potentially result in grid congestion problems in the network. Congestion occurs because the required distribution capacity surpasses the limits of the existing network [4].

In some areas this grid congestion issue will happen earlier than other due to differences in the expected EV adoption rates, and the grid characteristics [6]. Smart charging of EVs offers an alternative for better managing and incorporating the additional electricity demand of EVs within the power system. Smart charging can be defined as follows; optimizing the charging session by alignment of time, speed, and charging method with the EV-owner's preferences and given both electricity market and grid conditions.

The concept of smart charging has been tested in several contexts and pilots. 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 [7].

Preliminary results from one the largest smart charging projects (Electric Nation) which took place in the United Kingdom are also promising. Within the Electric Nation project about 700 EV-owners participated in pilot whereby they smart charge their EVs both at home. On weekdays one was able to reduce the charging rate by at least 25% (from 32A to 24A) per participant [8].

The results of aforementioned pilots are relevant but they do not 'represent' realistic smart charging behaviour due to the fact that smart charging happens within the context of trial. Jedlix is one of the few commercially available smart charging services whereby the EV-owners voluntarily install the app to charge their vehicles on 'beneficial' moment of day. The main objective of this research is to provide insights in the charging behaviour of EV-owners based real smart charging data which are collected via the Jedlix app. Furthermore, we aim to look at wide perspective and implications of smart charging based on the observed patterns from the historic data.

2 Dataset and Methodology

In this paragraph we describe the background of the input dataset, and the methods we applied to analyse the data.

2.1 Dataset structure

Table 1 includes an overview of data fields which have been used in this study.

Table 1: Overview of input dataset

Variable	Description:
User id	Hashed (anonymised) string which represent the EV user
Brand	Brand of the EV
Model	Model of the EV
Location type	Location where transaction took place (Home or other location)
Charging mode	Charging mode of transaction (AC or DC)
Transaction type	Type of transaction (Smart or Regular)
Transaction id	Unique transaction id
Start time	Start datetime of the transaction
End time	End datetime of the transaction
Duration	Duration of connection time
Energy demand	Total energy transfer per transaction
Power demand (maximum)	Power demand (maximum) per transaction
SoC at arrival	SoC at arrival of the EV

2.2 Methods

In this study we have analysed one of this first EV smart charging dataset based on real charging events at home and public and semi-public charging points. The main input data is an anonymised set of more than 10,000 detailed charging sessions. The dataset includes the complete charging records per user. So, due to the quality and the variety of the dataset we are able to analyse the charging behaviour of the EV-owners by quantifying multiple indicators. This research mainly applies an exploratory data analysis approach to describe the charging behaviour of EVs. Table 1 includes a short description of the seven indicators which are being quantified in this research.

Table 2: Overview of indicators

Indicator:	Description:
Connection time	Time of arrival of EV at the charging station.
Connection duration	The duration of the total plug time of EV at the station.
Energy demand	The volume of energy consumption per charging session.
Charging frequency	The number of charging sessions per unit of time (in this case per week).
State of Charge (SoC)	The initial state of charge at the start of connection time.
Charging curve	The charging rate of EV per SoC level.
Smart charging	In this case the impact of coordinated charging is measured by a comparison of energy demand within smart charging profiles versus non-smart charging profiles at certain time of day.

3 Results

This section contains the empirical results per defined indicator.

3.1 General characteristics

The main input dataset for this paper includes an anonymized charging details records of 140 different EV-owners whom are using the Jedlix application for charging their vehicles. Furthermore, all vehicles types are full electric passenger cars.

The data covers all charging sessions that took place in the year 2018 from this randomly selected EV owners. Based on this data we have analyzed the charging behaviour of the group by looking at the following indicators; connection duration, charging time, energy demand, power demand, state of charge, and charging frequency. In addition, also the impact of smart charging has been quantified based on real charging events. Finally, the results of this analysis have been validated by the overall charging behaviour of all Jedlix users.

In general, the charging events in the dataset can be divided into two different type of sessions;
Group A; Smart charging sessions (69% of the total records in the dataset); within these events the EV-owner choses for the default charging option of the Jedlix app which is smart charging.
Group B; Regular charging sessions (31%); within these charging events the EV-owner clicks on the 'override' button and selects for the option to charge the EV battery directly at start of the connection to a charging point.

Figure 1 shows the decomposition of the both types of charging events per month. From the figure we can observe that the share of smart charging sessions is steadily increasing from 62% in November of 2017 to 74% in June of 2018. Most probably, this is the result of getting better understanding of charging process, and more familiar to the Jedlix app by the users.

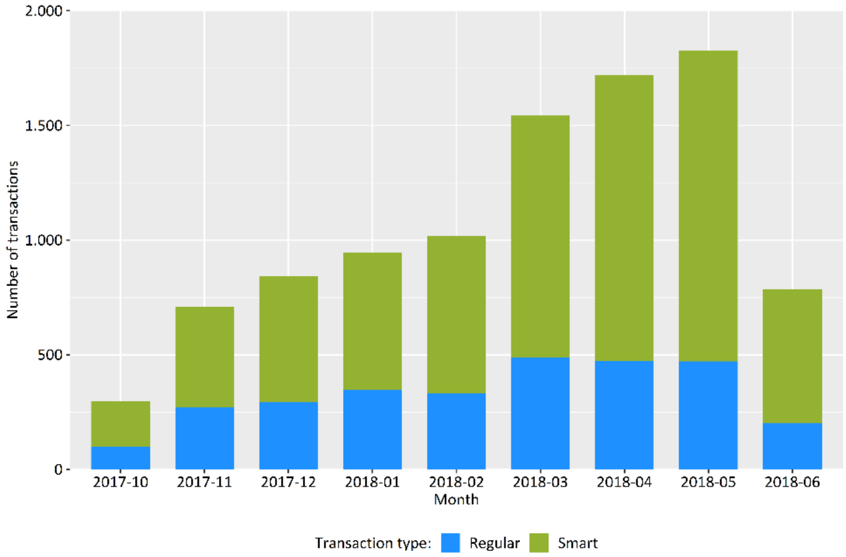

Figure 1: Transaction per month[1]

3.2 Connection time

Primarily, we have looked at the connection times of the sessions. So, we have quantified on which moment of the day the EVs are connected to charging points. Jedlix users can use the app at different locations.
The analysed charging sessions come from three location categories;

A. Home chargers; these are private charging points which are usually installed at EV-owner's dwellings. This category of charges are regular AC charging with maximum power supply of about 17.3 kW. About 54.4% of all charging records in the analysed dataset took place at home chargers.
B. Other locations; these are public and semi-public AC chargers. More than 36% of the charging sessions in the dataset have happened at this type of chargers.
C. Fast chargers; a small portion of the charging sessions belong to the category DC fast chargers whereby one can charge with rates from 50 kW. About 1,000 of charging sessions (9.2%) took place at DC chargers.

The figure below includes the distribution of charging session per location type based on their arrival time at the charging points. Within the first category of chargers (home chargers) we can observe a peak in the arrivals between 6 – 7 PM. Looking at the arrival times within the second category (other locations), we can see that about 22% of the sessions start around 9 AM at this type of chargers. There is a rational explanation behind this peak of arrivals in the morning because this category of chargers represent typical 'workplace' charging behaviour. Furthermore, the charging sessions at fast chargers happen during entire day with a minor peak around 3 PM.

[1] For the months of October 2017 and June 2018, the dataset contains fewer charging sessions because the analysed set does not cover the entire charging records of selected EV-owners for both months.

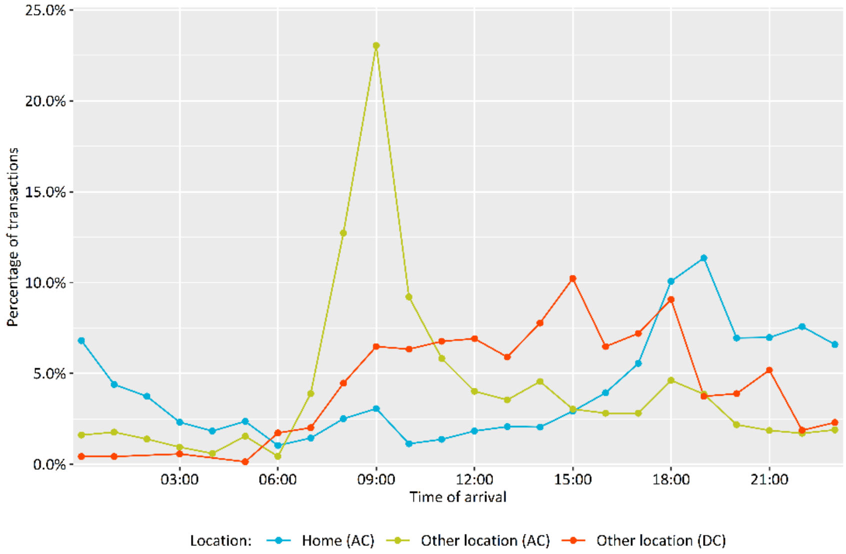

Figure 2: Distribution of arrival times

3.3 Connection duration

Secondly, we have looked into sessions duration; how long the EVs stay connected at the chargers per charging event. Figure 3 includes distribution of connection duration per location type. The majority of sessions (76.4%) at home chargers have durations more than 8 hours. In contrast, within the second category of chargers (other locations) less than 49% of the sessions have a duration of at least 8 hours. Thus, the share of longer lasting charging events is higher within the home charging sessions. In the category, the majority of charging sessions (about 70%) have duration of less than 2 hours.

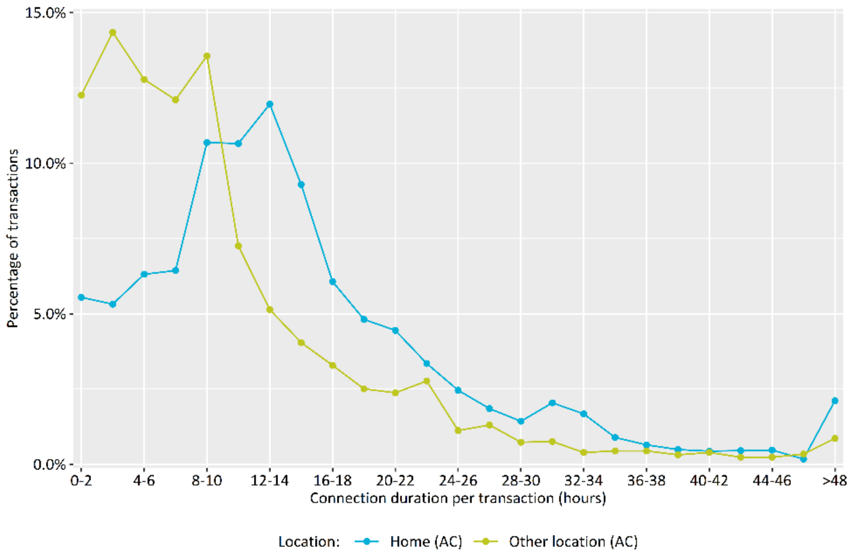

Figure 3: Distribution of session's duration

3.4 Energy demand

As third indicator, we have analysed the energy demand per charging session. Figure 4 depicts the distribution of energy consumption per session at each location type. Due to the fact that all charging session belong to full electric vehicles with high battery capacity, we can see that per charging event high volumes of energy is being delivered from stations into EVs.

Within the majority of the charging sessions at home, and other chargers (respectively 58%, and 63%) the energy demand is less than 32 kWh per event. The charging sessions at fast charging locations require more energy; about 62% of charging events consume energy volumes of at least 32 kWh.

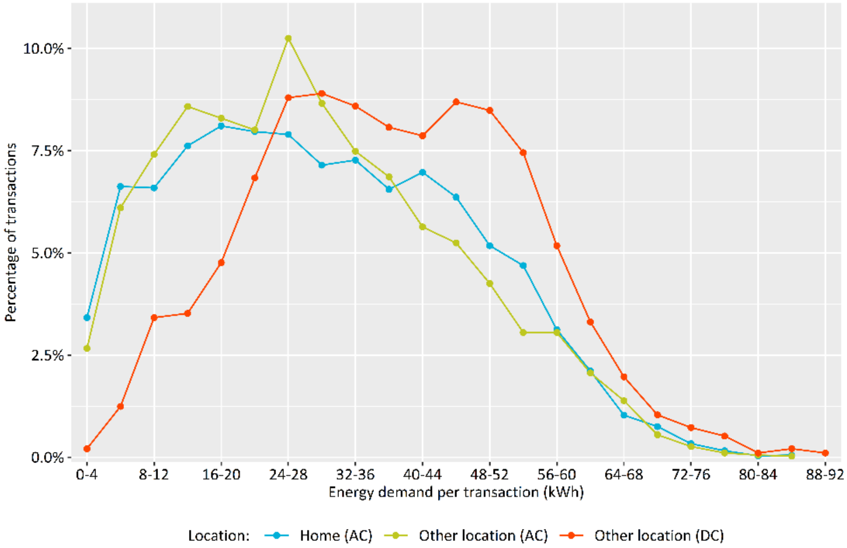

Figure 4: Distribution of energy demand

3.5 Charging frequency

In this analyses, we have also quantified how many times the EV-owners charge their vehicle per week. Figure 5 visualizes how many charging events on average (orange dot) each EV has per week, regardless of the charging event's location. Furthermore, beside the average indicator we have also looked in the standard deviation (vertical line) of charging frequency per week. On average each EV-owner plugs in the vehicle about 4 times per week for recharging the battery with an average standard deviation of about 2 charging sessions per week.

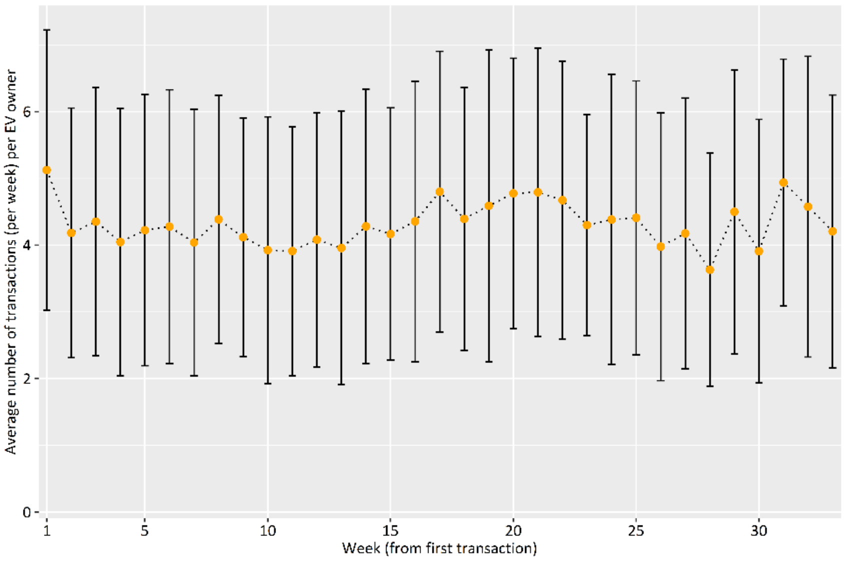

Figure 5: Distribution of charging frequency

3.6 State of Charge

The energy demand per charging event is partly determined by the state of charge (SoC) level of the battery at the start of a charging session. Figure 6 illustrates the average, and the standard deviation of SoC level at the time of arrival per location type. Within the first two category of chargers (home, and other locations), we can see that the EV batteries are half full (with standard deviation of +/- 25%) at the time that EVs are connected for a recharge. Furthermore, from the dataset we observe that the mean SoC level is about 38% for sessions at fast chargers with standard deviation of 19%. In general, we can conclude that the EV-owners do not postpone the charging of the their vehicles till the battery is full empty (low SoC).

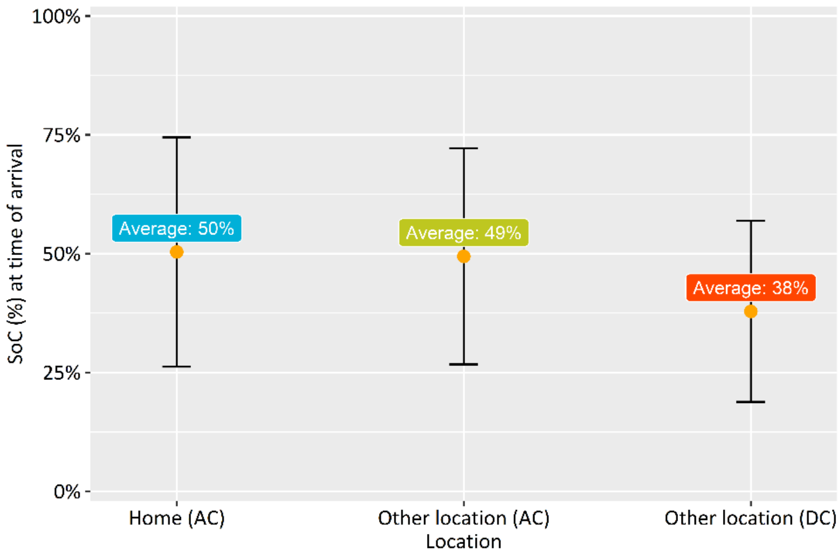

Figure 6: Initial SoC level per location type

3.7 Charging curves

The input dataset for this analyses also includes the intermediate meter readings within each sessions. Hence, it also possible to look into the charging curves of EVs; the charging rates at each SoC level. Figure 7 shows the average charging profile at AC chargers (home, and other locations). So, in the graph we depict the charging power (vertical axis) against the SoC (horizontal axis) with an interval of 5%. Additionally, also the standard deviation in charging rate is added per SoC interval. Finally, also the number of charging events per SoC interval measurement (gray points) are included. This latest variable can be seen as a proxy for reliability of the charging profile. By adding this feature, we can notice that in some cased the average charging rates is based on data from 250 different charging sessions while in other cases the average charging power derived from measurements of 6,000 different charging events.

In general, one can observe that the mean charging power will start decrease rapidly from 75% SoC level. This decrease in the charging rate has two main causes. First, in the data we can notice that every EV model has a slightly different charging curve. Second, although all charging events happen at AC chargers, it can be the case that different chargers have their own characteristics in terms of maximum power capacity, and allocation of power in case of dual charging (both socket are occupied at the same time).

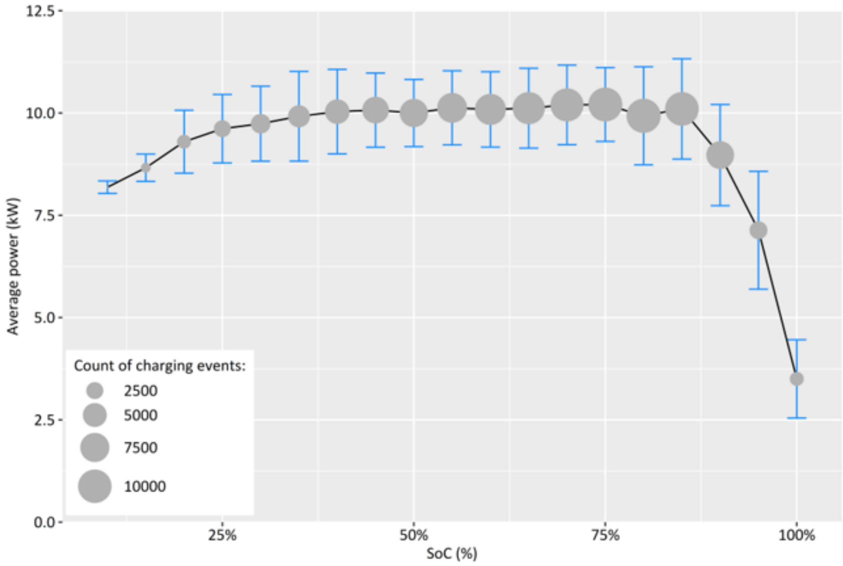

Figure 7: Charging curve

3.8 Smart Charging

Finally, we have quantified the impact of smart charging. As stated earlier, the dataset included two type of transactions; smart, and regular events. In order to measure the impact of smart charging versus regular charging we have selected 1,000 random charging events from each type. The transactions are selected from the same period; April, and May 2018. This filter has been applied in order to omit any weather related influences on the comparison. Within this period of two month we have summarised the total energy demand per group of transaction on hourly bases. The outcome of this aggregated profile is included in figure 8.

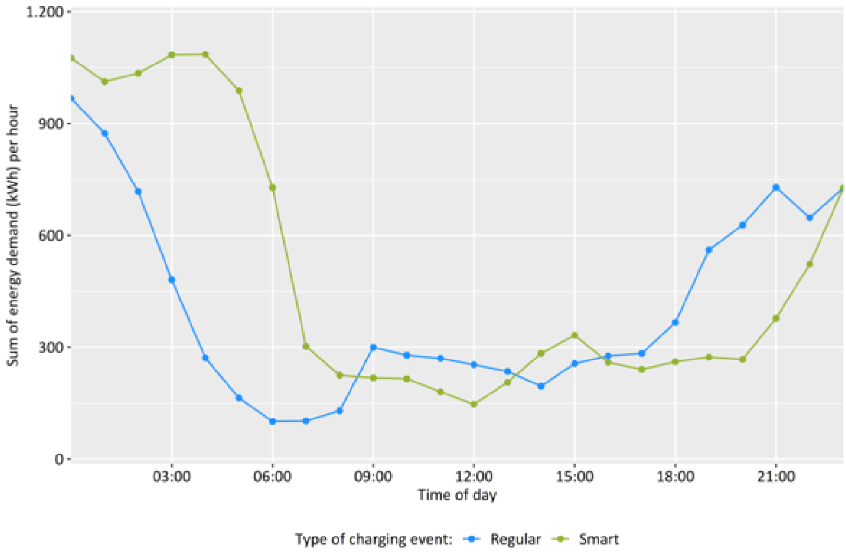

Figure 8: Impact of smart charging

Overall, from the figure we can see that the smart charging sessions demand less energy during in the morning, and in the evening peak. Furthermore, from the graph it is also visible that the total energy demand of smart charging events shift to nightly hours. Focusing on the evening peak (between 18:00 – 21:00), we can conclude that smart charging results in 47% lower energy demand compared to regular charging. Based on this outcome we can assume that within the context of Jedlix optimization, smart charging results in lower evening peak on the LV electricity grid. In figure 9 we put this outcome in perspective by comparing the energy consumption for each type of transaction with the average electricity demand of households in the

Netherlands [9]. We have normalized the energy demand from each consumption type in order to make the comparison possible. Furthermore, we have stacked the lines for EV charging types to indicate the increase in household consumption in both charging types. Focusing on the evening peak (between 6 and 9 PM) we notice that within the regular charging transactions the total demand (EV + household) increase more than 100% comparing to average household demand which is assumed as the baseline here. With smart charging there is an increase of about 45% comparing to household demand during the evening peak. Thus, from this observation we can assume that smart charging results in less higher peaks during the evening peak.

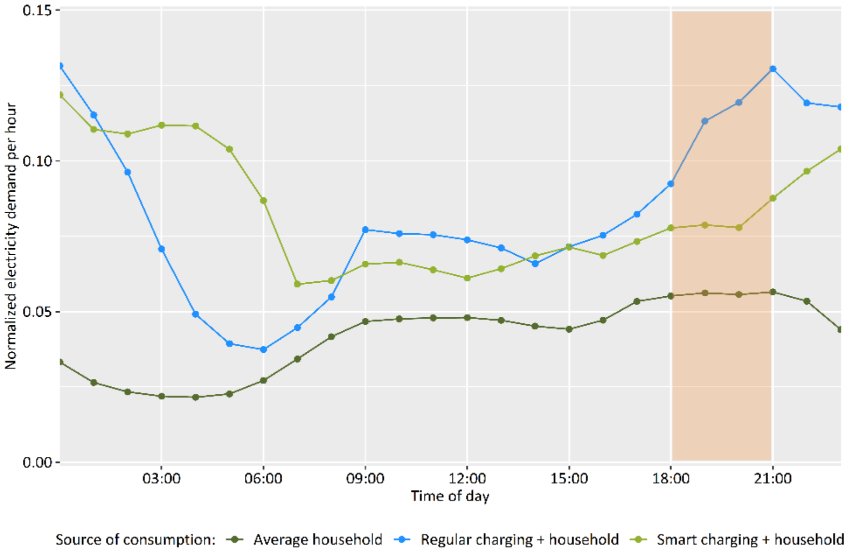

Figure 9: Comparison of household demand and EV demand

4 Conclusion and discussion

This research aims to describe the charging behaviour of EV-owners participating in smart charging via the following indicators; connection times, connection duration, energy demand, charging frequency, state of charge of EVs, charging profiles, and the impact of smart charging. The results of this analysis seem promising for avoiding peak demand of electricity at the LV grid via smart charging of EVs.
The results of this explanatory analysis can be summarised as follows;

- The analysed dataset includes mainly smart charging sessions (69 %).
- On average each EV-owner has a charging frequency of about 4 times per week.
- It stands out that the majority of the EVs start with new sessions at relatively high SoC (about 50%).
- From the AC charging curves we can observe a slight decrease in the charging rate from 75% SoC.
- Based on the analyses that we can indeed confirm that EV-owners go for fast charging at lower levels of SoC, compared initial SoC within regular AC charging sessions.
- From a comparison of 1,000 randomly selected smart charging events with 1,000 regular sessions appears that between 6 – 9 PM (evening peak) the smart charging sessions energy demand is 47% lower compared to the energy consumption of regular charging. Based on this sample, smart charging seems to omit significant increase in electricity demand of household during the evening peak.

In general, the outcomes of this study show that smart charging can be a 'effective' instrument in order to prevent higher peak demand on the LV grid. However, these results are based on usage pattern of selected group of EV owners whereby they posses over EVs with high battery capacity, and relatively high willingness to allow smart charging of their vehicles. In order to generalise these results more observations from broader type of EV-owners is needed within different smart charging conditions. Also, the impact newly created peaks on the LV grid should be investigated, and how the national electricity demand profile will be shaped once he charging of large volume of EVs is optimized based on certain target (e.g. grid congestion or low electricity price).

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