Individual EV load profiling and smart charging to flatten total electrical demand

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Abstract. The rapid growth of electric vehicles (EVs) is stimulating their integration into the existing power grid to reduce power peaks and avoid grid congestion using smart charging strategies. Specifically, at commercial buildings, most EVs charge simultaneously in the morning resulting in large power peaks. This uncoordinated EV charging is changing the existing building load profile, which already fluctuates due to HVAC operations and PV fluctuations, significantly with their dominant charging load by amplifying power peaks. The changed building load profile of a single building does not influence the grid significantly, but the cumulative power peaks at commercial buildings can cause grid congestion. Smart charging can solve this problem by regulating power rates of charging sessions to anticipate the electrical building load. Therefore, this research aims to evaluate individual EV charging load profiles, based on real-world data, and the smart charging potential to flatten the total electrical load of a case study. Daily charging load profiles are constituted with k-means data clustering techniques to obtain the general charging profiles of individual EVs for deploying smart charging strategies. Additionally, the HVAC load flexibility potential is explored to complement smart charging with load flattening. The smart charging potential showed promising results with individual power peak reductions up to 37.8% and an average power peak reduction of the total EV load of approximately 60%.

Keywords. Electric vehicles, EV load profiling, smart charging, demand side management, load flexibility.
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1. Introduction

Electric vehicles (EVs) are increasingly adopted as an alternative for internal combustion engine vehicles (ICEVs) to comply with the Paris Agreement on climate change aiming to reduce CO_2 emissions. It is expected that the Dutch EV fleet will increase from 0.21 million in 2021 to approximately 4-5 million in 2035 [1-3]. Besides the rapid growth, EVs often charge at their maximum power rate until the battery is fully charged, which can be characterized as uncoordinated charging. The growing EV fleet in combination with uncoordinated charging, result in an increasing power demand, power peaks and demand variability. For grid operators, it becomes more difficult to accurately predict the required load, which endangers the reliability and quality of the power supply [4,5]. Specifically, at commercial buildings, EVs can create a problem since typical occupancy patterns are noticeable, where employees arrive in the morning and depart late in the afternoon [6]. The occupancy pattern in combination with uncoordinated charging results in power peaks in the morning and long idle times in the afternoon. This uncoordinated EV charging is changing the existing building load profile, which already fluctuates due to HVAC operations and PV fluctuations, significantly with their dominant charging load by amplifying power peaks. However, EVs can offer significant load flexibility with smart charging and thereby regulate the voltage frequency of the grid or on a smaller scale the voltage frequency of a building [7,8]. The generally long idle times of EVs at commercial buildings enable load shifting by scheduling the load over the entire workday to flatten power peaks. Complementary to smart charging strategies, HVAC systems can assist with grid balancing by throttling the power rate without affecting occupants' comfort [9,10]. Therefore, it is of major importance to gain knowledge about the individual EV charging behaviour and the potential load flexibility of HVAC systems to accomplish smart charging strategies.

2. Literature review

This section describes some approaches that have been used for load profiling of EVs, smart charging scenario and the underlying assumptions that have been adopted.

Real-world EV charging datasets are scarce, resulting in research [11,12] that use travel patterns of conventional cars – often retrieved from national surveys – in combination with EV characteristics assumptions to constitute EV charging load profiles. Therefore, these studies could only rely on the parameter parking duration. and assumed other parameters, such as charging power, idle time and battery capacity. The assumptions of EV charging behaviour in these studies cause significant uncertainties. Fortunately, real-world data becomes widely available due to the increasing growth of EV adaptation. Researchers [13-17] have used historical data of EV charging events to constitute EV charging load profiles. The most important parameter found in the literature to constitute proper EV charging load profiles is the average charging power per time interval of maximum 15 minutes. Other parameters, such as connection duration, charging time, idle time and energy consumption, can be obtained with the charging power per time interval. Moreover, the initial and final state of charge (SoC) are valuable parameters found in the literature [15-17]. These parameters are useful to schedule charging events and to determine the charging sequence with smart charging strategies. However, it should be noted that the availability of SoC values depends on the charging protocols. DC-chargers – used for fast chargers – can obtain SoC values, where AC-chargers cannot obtain SoC values with the current widely applied IEC 61851-1 protocol. Fortunately, SoC values could be available for AC-chargers with the new ISO-15118-20 protocol and the cooperation of original equipment manufacturers (OEMs) in the near future [18]. In the existing literature, the generation of general EV load profiles are based on averages of large datasets and EV fleets. This paper distinguishes itself by collecting and evaluating the individual load profiles of EVs at a commercial building per weekday.

After investigating the EV charging behaviour, smart charging scenarios can be constituted. Flattening power peaks to secure the reliability of the grid is the most important objective of smart charging. Ref. [4] investigated the impact of smart charging on the transmission and distribution lines of Great-Britain. The smart charging focused on unidirectional charging with a maximum of 7 kW, an efficiency of 90% and charging based on SoC values and the electricity price. According to this strategy, EVs charge at off-peak hours when the electricity price is low. At peak hours when the prices are higher, EVs with a low SoC still charge at a higher rate, while EVs with a higher SoC does not charge or charge at a low rate. This smart charging strategy can reduce network intervention from 28% to 9%. Ref. [8] investigated peak shaving and valley filling of a university building with an EV parking lot. The study focused on a tool to monitor the occupancy at the parking lot by registering the arrival and departure times of conventional cars. By knowing the required energy for the next trip, based on user preference, and assuming that EVs have a battery capacity of 24 kWh and charge/discharge slowly, power peaks could be reduced by approximately 20%. In addition to Ref. [8], Ref. [19] investigated the peak shaving and valley filling of the same university, but this time with PV panels. In the most ideal situation of this scenario, the power peak could be reduced by approximately 25%. Ref. [20] developed a smart charging/discharging schedule algorithm aiming to peak shave and valley fill the power load profile of the grid. This study considers several constraints related to EVs. First, charging and discharging rates must be within maximum and minimum values to avoid battery degradation. Second, batteries must be charged up to a maximum limit and discharged to a set depth of discharge (DOD). These limits can be set by the EV owner. In Ref. [21] a smart charging strategy is compared with uncontrolled charging. The smart charging strategy uses price signals and the SoC of the EVs as input to determine the charging power output, assuming an initial SoC of 20% and a charging rate of 6.6 kW.

Most studies [7,19-21] use SoC values to constitute smart charging strategies, however, this paper purely focuses on historical EV charging rates and the interaction with the electrical building load. The historical charging rates are used to constitute EV charging load profiles, which are valuable to obtain a better understanding of the individual and aggregated charging behaviour, such as charging power, charging time, idle time and presence, without compromising the privacy and convenience of the EV owner. Not using SoC values is more representative to reality, since SoC values are currently not available with AC/DC charging due to a lack of protocols. Therefore, this paper distinguishes itself by investigating load profiles of individual and aggregated EVs, flattening the power demand using smart charging and by evaluating the energy flexibility capability of the HVAC system at a case study. To that end, the main contributions of this work can be summarized with the following research questions:

- What are important parameters to constitute appropriate EV charging load profiles?
- What are the characteristics of the individual and total EV charging loads at the case study?
- How large is the smart charging potential of the case study?

The rest of the paper is organized as follows: Section 3 describes the case study, methodology of load profiling and determination of the smart charging potential. The results of the smart charging potential and the HVAC flexibility are presented in Section 4. The discussion about the obtained results is presented in Section 5. Finally, conclusions are drawn, and recommendations are provided in Section 6.

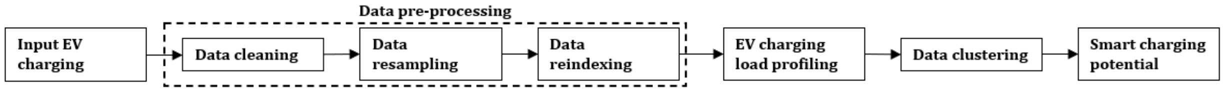

Fig. 1 – Stepwise process of the research.

3. Methodology

In this section, the process and used methods in this study are explained in detail. The sequence of the process is illustrated in Figure 1.

3.1 Case study

The office building of Kropman Breda is used as case study and can be characterized as a traditional Dutch office building. The HVAC system consists of a gas-fired boiler and an air handling unit (AHU) which controls the ventilation, cooling and humidification demand. Additionally, a photovoltaic (PV) system is installed in combination with a battery energy storage system (BESS) to increase self-consumption. Moreover, the case study contains two EV chargers each with two charging sockets. Both EV chargers are 3 phase 32 A and connected to a voltage of 230 V. Therefore, a single charger has a maximum power output of 22 kW (3 * 32 A * 230 V = 22,080 W = 22 kW). When an EV plugs in, it communicates with the Electric Vehicle Supply Equipment (EVSE), EV charger, according to the IEC 61851 protocol. This protocol only supports unidirectional energy exchange, thus, EVs can only charge their battery. The EV charger communicates its maximum power output to the EV and the EV communicates its maximum charging rate to the EV charger. Then the actual charging rate is determined by the lowest maximum charging rate. Data of the charging event is transferred from the EV charger to the charge point operator (CPO) where the data is collected. In addition, the CPO can set charging profiles for individual EVs via the Open Charge Point Protocol (OCPP).

3.2 Data acquisition

The used datasets are obtained from the EV chargers of the investigated office building and contain approximately six months of data (November 2020 – May 2021) from five EVs in total. The datasets only consist of unidirectional charging events, since discharging with bidirectional charging events is currently not supported by most EVs. The datasets are log data and contain a lot of parameters, but only data about datetime, charging rate (kW) cumulative energy consumption of the charging session (kWh) and ID number are relevant. The ID numbers are necessary to differentiate data from individual EVs in the pre-processing phase, whereas the charging rate is used to constitute load profiles and energy consumption is used to obtain some general insights, such as average charging time.

3.3 Data pre-processing

The first step is to clean the data by filtering valuable information. The second step involved the resampling of the data. The datasets are down sampled to 15 minutes time intervals to replace the irregular time intervals from the log data, since regular time intervals are necessary for the constitution of representative EV charging load profiles. Finally, the datasets are reindexed to create similar time series.

3.4 Constitution of load profiles

K-means data clustering is used to extract clusters which represent common daily load profiles. The number of clusters are validated with two different methods. The first method is the silhouette score. The silhouette value is a measure of how well an object fits in its own cluster in comparison to other clusters. The silhouette score can vary between +1 and -1. A value close to +1 indicates a good match, a value close to 0 indicates overlap between the clusters and a value of -1 indicates a mismatch of clusters. The second method is the elbow method. This method calculates the Within-Cluster Sum of Square (WCSS) for different amounts of 'k' clusters. WCSS is the sum of squared distance between each point and the centroid in a cluster. With an increasing amount of 'k' clusters, the WCSS decreases. The optimal number of clusters can be determined by plotting the WCSS of all clusters. The optimal number of clusters according to the elbow method can be recognized when the graph bends and the decrease of WCSS stagnates.

3.5 Smart charging scenario

Based on knowledge about the electrical building load, a smart charging scenario is proposed to determine the smart charging potential of the case study. The scenario aims to flatten the EV charging load, since the electrical building load is already flattened due to operations of the photovoltaic (PV) system in combination with the battery energy storage system (BESS). Multiple assumptions are made to simplify the scenario:

- A default charging threshold of 7 kW is set for the individual cars, based on assumptions from earlier research [4].
- The maximum charging power is limited to 14 kW, which corresponds to two EVs charging simultaneously at the default charging rate.
- Only 'morning' clusters of the EVs are evaluated. The morning clusters seem most realistic because earlier research [6] indicates that most

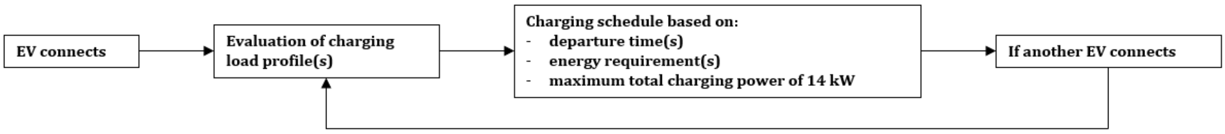

Fig. 2 – Smart charging scheduling.

power peaks occur in the morning.

- The energy requirements of an EV are determined with the integral of the investigated cluster according to the equation (1):

$$E_{e;d} = \int_{0}^{48} P(t)\,dt \qquad (1)$$

$E_{e;d}$ = energy consumption of a specific EV (e) at a specific weekday (d) [kWh]
$P(t)$ = average power demand in 15 minutes time interval [kW]
t = time [1/4 h]

- The number of charging events throughout a week is assumed to be worst-case, meaning that an EV charges at all workdays on which it has charged previously.

The charging sequence is based on priority by continuously monitoring the presence and energy requirements of EVs as illustrated in Figure 2.

4. Results

4.1 Exploratory data analysis

Initially, the pre-processed dataset is explored to obtain an indication of the individual EV charging load profiles. A boxplot of the charging power and energy consumption provides valuable insights about the general charging power, energy consumption and charging duration. From the charging power distribution in Figure 3, it is noticeable that EV 1-3 have overlapping quartiles, indicating uncoordinated charging patterns at maximum power rate (11 kW). Contrary, wider ranges for charging rates are noticeable for EV 4 and 5, indicating some kind of 'manual smart charging'. Moreover, the average energy consumption varies between 25 – 30 kWh approximately according to Figure 3. The charging power and energy consumption combined, roughly indicates an average charging duration between 2.5 – 4 hours.

4.2 EVs load profiles

The exploratory analysis shows valuable insights. However, important daily and quarter hourly information is missing, thus, daily load profiles based on quarter hourly data are necessary for more detailed information. In general, it is noticeable that all EVs have quite similar clusters. Most EVs have two clusters, where one cluster starts charging in the morning, stops charging after several hours and has a relatively long idle time. The other cluster, which is not considered in this study, starts charging later in the morning or in the afternoon and has almost no idle time.

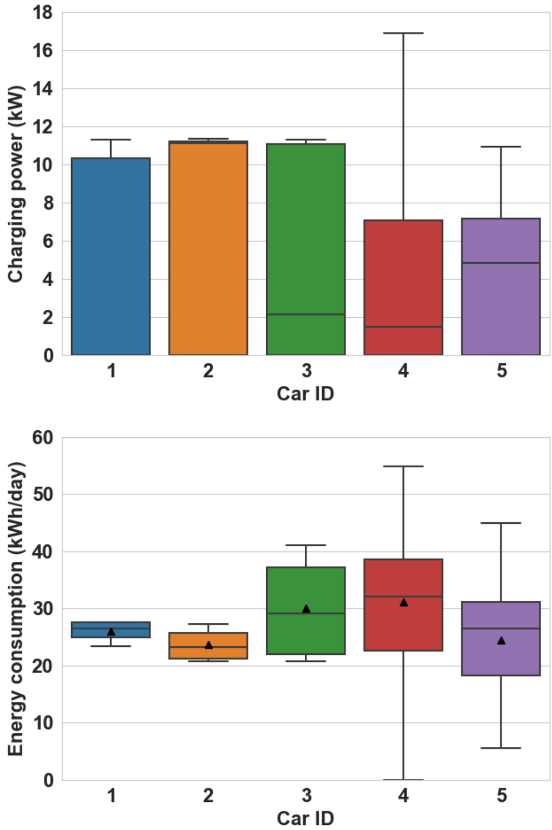

Fig. 3 – Charging power distribution of individual EVs (top) and energy consumption distribution (bottom).

4.3 Comparison between building load and total EV load

The total EV load contains four clusters of which three clusters can be characterized as 'morning cluster', one cluster as 'afternoon cluster' as illustrated in Figure 4. The outcome is comparable with earlier research [6] and empowers our assumption to focus on morning clusters. Moreover, it is noticeable that the power peaks of the total EV load are occasionally larger than the electrical building load of the case study, depending on the buildings' cluster and the EV's cluster, which emphasizes the importance of smart charging. In addition, quick ramp ups and downs of the EV load are noticeable during office hours (07:30-17:30 h) due to arriving, departing employees and fully charged batteries, whereas the building load has only one quick ramp up before the office hours and one quick ramp down before the end of the office hours.

4.4 Smart charging potential

The smart charging potential at the case study is evaluated by comparing EV charging loads

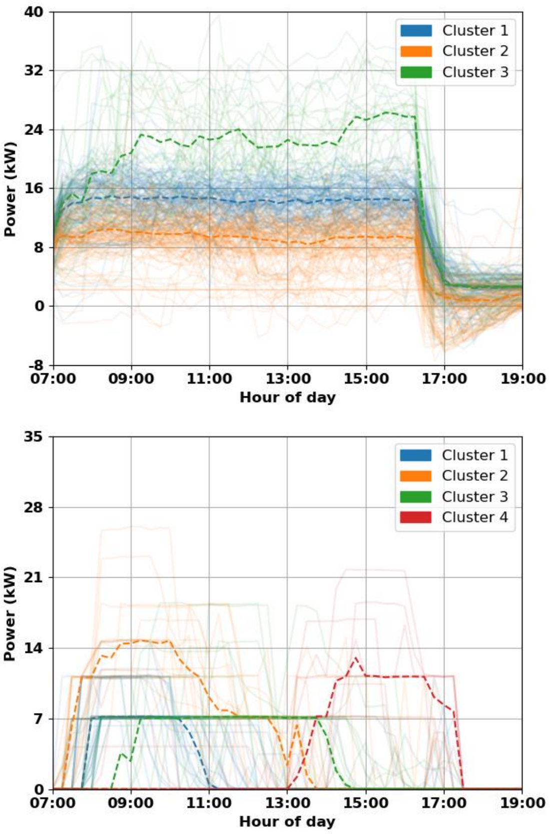

Fig. 4 – Comparison between electrical building load (top) and total EV charging load (bottom).

according to uncoordinated and coordinated charging sessions, using real-world data. The proposed smart charging scenario aims to flatten the EV load since the electrical building load is already flattened. Overall, it is possible to reduce the power peaks in the morning by spreading the EV load over the day. Load shifting is arranged by limiting the charging power and delaying the charging sessions on individual level, where its applicability depends on the connection time and required energy. The smart charging potential is evaluated per weekday during a typical week as illustrated in Figure 5. The average individual power peak reductions vary from a slight decrease of 2.83% up to 37.8%, where the average power peak reduction of the total EV load equals 59.6% as shown in Table 1.

4.5 Potential HVAC flexibility

In addition to the load flexibility of smart charging, the load flexibility of HVAC systems is considered. Especially at critical days when a lot of EVs charge simultaneous with inevitably large power peaks, complementary load flexibility from the HVAC system could be desirable. Earlier research [9,10] investigated the load flexibility potential of the ventilation fan, chiller and humidifier at our case study. They found a significant potential to reduce the power demand by adjusting the active operation, without affecting indoor comfort and human health, as shown in Table 2.

Tab. 2 – Characteristics of HVAC load flexibility.

Criteria	Ventilation	Chiller	Humidifier
Response time [min.]	0.5 – 5	5	5
Availability duration [min.]	120	20	60
Power reduction [kW]	4	7	14
Energy reduction [kWh]	8	2.3	14

The load flexibilities of the ventilation fan and humidifier are suitable for complementary power reductions, since the response time is fast, the availability duration is long and the power demand is arranged with proportional integration derivative (PID) controllers. In contrast, the chiller is less suitable for complementary load flexibility since the power demand is controlled per stage and the availability duration is short. The HVAC load flexibilities are currently not incorporated in our smart charging strategy, because further research is necessary to investigate the controllability of HVAC components within smart charging strategies.

Tab. 1 – Numerical overview of smart charging results ('-' indicates absence).

EV load	Monday	Tuesday	Wednesday	Thursday	Friday	Average
EV 1	–	−37.7%	−37.8%	–	–	−37.8%
EV 2	–	–	−37.7%	−23.9%	−11.0%	−24.3%
EV 3	–	−37.7%	–	–	−22.2%	−30.0%
EV 4	−24.4%	+0.24%	−37.1%	−1.19%	−37.1%	−19.9%
EV 5	−2.45%	−3.06%	−2.89%	−2.80%	−2.94%	−2.83%
Total	−57.4%	-61.5%	−63.4%	−63.1%	−52.4%	−59.6%

5. Discussion

The results of the smart charging potential are very promising. However, the smart charging potential is accompanied by certain uncertainties and limitations which will be described in this section.

First, the used datasets have a limited number of charging events. Only 122 charging sessions are registered since the operation of the EV chargers. A larger dataset would increase the reliability of the clustered charging profiles.

Second, in most cases it is unknown how much energy an EV needs to charge, since SoC values are often not available due to a lack of open protocols. Therefore, this study determined the energy requirement of an EV at a specific weekday by the integral of the obtained cluster.

Finally, assuming that EVs charge at all weekdays on which it has previously charged, probably results in a significant overestimation of the charging load, since it is unlikely that an EV always charges when present. The presence of a single EV is investigated and compared with charging sessions from the datasets. This particular EV only charges 52% of the time. Therefore, it is plausible that this presence-charging ratio is also applicable to other EVs. Unfortunately, it was not possible to investigate the presence of other EVs due to privacy issues.

6. Conclusions and recommendations

6.1 Conclusions

Motivated by a lack of research regarding individual EV load profiling and smart charging, this research aims to evaluate individual EV charging load profiles to flatten the total power demand of a commercial building. Conclusions of this study are drawn by answering the defined research questions from section 2.

What are important parameters to constitute appropriate EV charging load profiles?

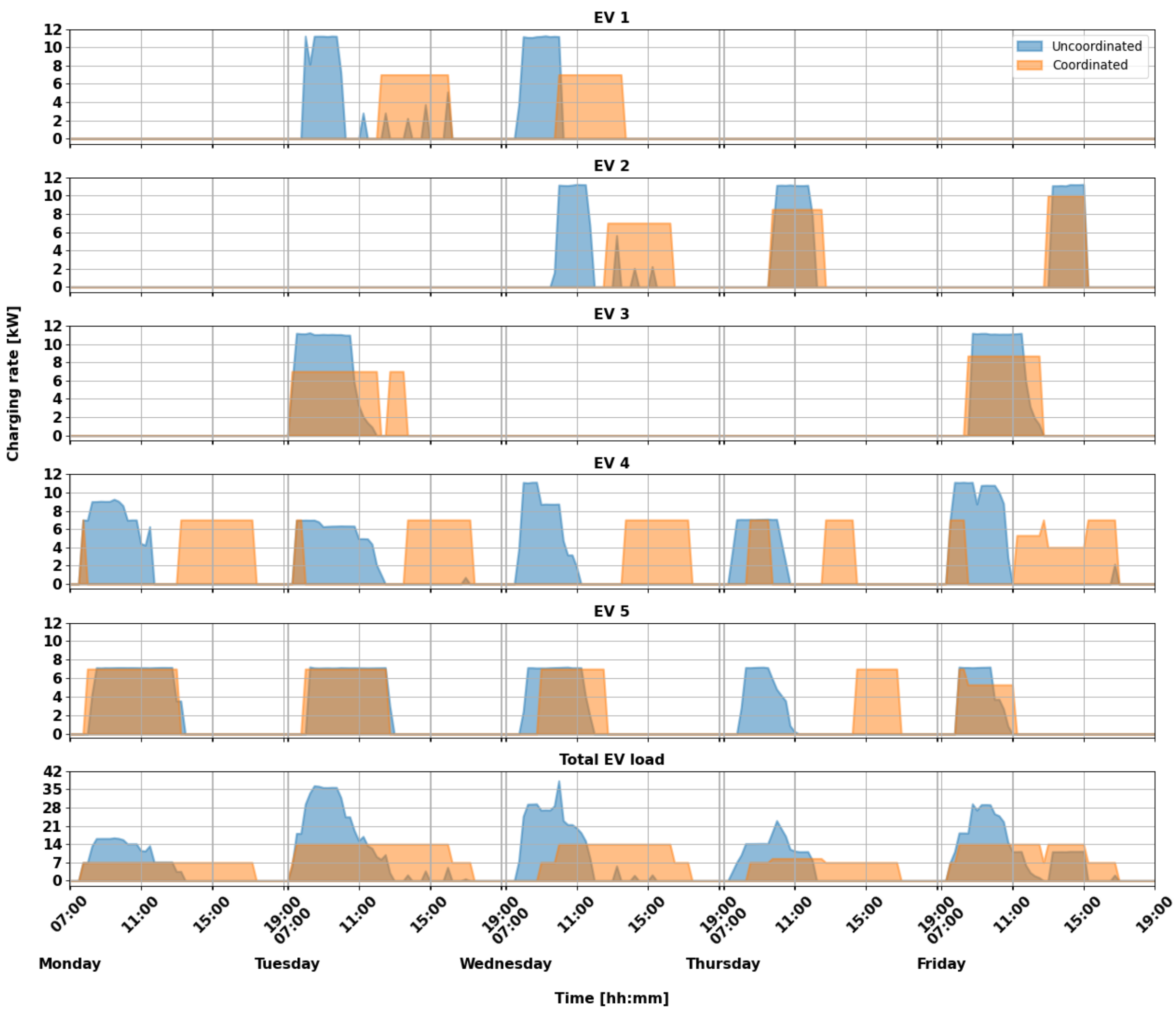

Fig. 5 – Visual overview smart charging potential.

It can be concluded that charging power per time interval is the most important parameters for the constitution of EV charging load profiles since other parameters can be retraced with the charging power. Additionally, initial and final SoC are key parameters for optimizing smart charging. Unfortunately, SoC values are often not available due to a lack of open protocols.

What are the characteristics of the individual and total EV charging loads at a commercial building?

Generally, it is noticeable that EVs often have two clusters, a morning and afternoon cluster, which are quite similar for all EVs at the case study. The morning cluster starts charging in the morning, stops charging after several hours and has a relatively long idle time. The afternoon cluster starts charging later in the morning or in the afternoon and has almost no idle time. Especially, the morning cluster enables smart charging by shifting loads to the afternoon to reduce power peaks. This holds for EVs with just a few charging sessions, but also for the EVs with relatively a lot of charging sessions. Moreover, the total EV charging load has four clusters and can also be distinguished in morning and afternoon clusters. three from the four clusters are morning clusters, which emphasizes the occurrence of power peaks in the morning.

How large is the smart charging potential of a commercial building?

To quantify the smart charging potential at a commercial building, power peaks of uncoordinated charging profiles are compared with coordinated charging profiles. Power peak reductions of individual and total EV load per weekday (Monday-Friday) are evaluated. Overall, it is possible to reduce the power peaks in the morning by spreading the EV load over the day. The average individual power peak varies from a slight increase of 0.24% to a decrease of 37.8% and the average power peak reduction of the total EV load equals 59.6%. Therefore, the smart charging potential of this scenario shows very promising results.

6.2 Recommendations

This exploratory research on individual EV load profiling and smart charging is the basis for more sophisticated research on smart charging. Therefore, this section provides the following suggestions for further research:

- In this study, data about EV charging and presence is limited. For further research, it is recommended to collect more data.
- Only one scenario is investigated in this research. However, there are more interesting scenarios to investigate. For example, a scenario without BESS since most commercial buildings do not have a BESS. Without BESS, the building load differs since energy storage is not possible. In this scenario, the scheduling of the charging load would mainly depend on the electricity production of the PV system to increase self-consumption.
- It would be interesting to implement the complementary load flexibility of the ventilation fan and humidifier into smart charging scenarios.
- The next step would be to create forecast models to predict the EV charging load a day-ahead. The forecast models would increase the accuracy and possibilities for smart charging strategies. It would be interesting to create two types of forecasting models: a forecast model to predict individual EV loads with detailed data and a model to predict the aggregated EV load of a larger population with limited data.
- After constituting a forecast model, optimization techniques could be used to find optimal smart charging scenarios and charging power rates. In this study, a default power rate of 7 kW was assumed, but with the application of optimization techniques, optimal power rates can be determined, which are based on the forecast of the building load and the presence of EVs.

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Data Statement

The datasets generated and analysed during the current study are not publicly available because of privacy issues.