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An empirical analysis of electric vehicle charging behavior based on real Danish residential charging data

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ABSTRACT

In the last two years there has been a significant increase in the global adoption of electric vehicles (EVs). Particularly in Denmark, 40% of new vehicle registrations in 2023 were electric, marking a notable shift towards e-mobility. As a result, EV loading begins to constitute a large part of residential electricity demand. The concurrent increase in the interest for reduction in charging costs via demand response leads to a growing need for better understanding of charging behavior and its impact on consumption profiles. This works addresses the lack of up-to-date large-scale empirical studies on residential EV charging behavior. It presents a thorough analysis of all important charging characteristics based on a large set of 5534 Danish residential chargers between 2021 and 2023, providing unique insight in the effect of user-induced controlled charging. Our analysis shows the difference between actual charging profiles and those commonly used by distribution system operators in Denmark, and reveals the significant change over the span of one year with the doubling of peak demand per charger from 1.25 kW to 2.5 kW.

1. Introduction

The adoption of e-mobility is accelerating at an unprecedented pace. Fig. 1 shows the evolution of the share of plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) in total new monthly registrations in Denmark [1]. In 2023, electric vehicle (EV) sales accounted for 40% of all new car registrations, with approximately 80% of those being BEVs. The need for a deeper understanding of EV charging characteristics is more pressing than ever. Technological developments, the use of smart charging features and higher electricity prices have led to a substantial change in EV consumption patterns and user behavior. Various stakeholders such as researchers, distribution system operators (DSOs) and transmission system operators, energy regulators, technology providers etc., need up-to-date empirical investigations to conduct EV studies related to power system applications.

A large number of such investigations of EV user behavior and charging patterns exists.[1] However, most of them do not rely on real EV charging data [2]. Further, various studies were based on early adopters or various trial/project participants whose behavior may often deviate from the broader population of a country. Additionally, user behavior evolves over time due to technological changes such as increasing battery sizes and wider availability of smart charging options [3]. Further, it has been suggested that EV users adapt their behavior as they become more experienced, and are gradually more comfortable to charge less often and at lower state of charge (SOC) values [4]. The recent dramatic fluctuations of electricity prices in Europe have also increased awareness with regards to charging energy costs. In this work, we provide a detailed up-to-date analysis of EV charging behavior and resulting load profiles based on a large number of residential EV users using real data from 2021 to 2023 and a set of 5534 chargers.

1.1. Related work

Only few empirical studies on residential EV charging behavioral analysis have surfaced so far, and the existing ones rely on very limited data sources. As stressed in [5], many studies rely on average statistics and hypotheses to study the impact of EV loading. While the author tries to address these issues with a detailed bottom-up approach that combines various data sources, the work still relies on assumptions (such as uncoordinated immediate charging upon plug in). As we show next, this assumption does not hold and actual EV charging data are needed to differentiate between a plug-in event and the start of the charging process. Therefore, detailed and updated EV charging

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[1] By EV user behavior we refer to plug-in and plug-out times, energy consumed in each charging session, the use of smart charging features etc.

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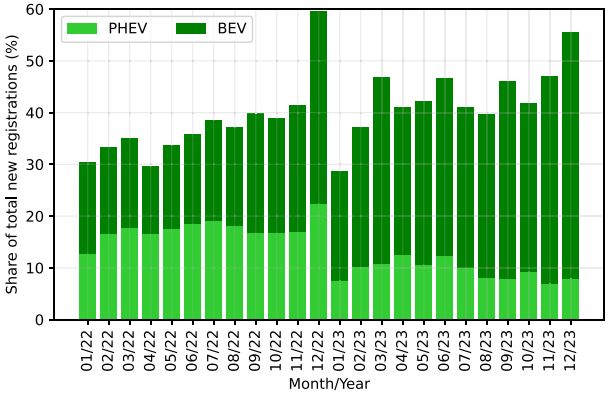

Fig. 1. Evolution of the share of BEVs and PHEVs in total new registrations per month in Denmark.

data are crucial to understand and study the impact of e-mobility on electricity consumption. To the best of our knowledge, there exists no comprehensive empirical study on residential EV charging in Denmark based on large-scale real data.

The authors of [6] made long-term projections for electricity consumption in Danish municipalities. They recognized the importance of EV consumption in 2040 but relied on simple assumptions to derive basic EV charging profiles because of data unavailability. The authors of [7] analyzed hourly metered data from only 14 households with an EV, 32 public charge stations and one fast-charge station in Denmark for the year 2018. As the authors state, such a sample is very small to draw conclusions related to charging behavior. On the contrary, the authors of [8] analyzed hourly smart meter data from 670.000 Danish households from 2017 and derived consumption profiles of groups depending on a number of characteristics such as income, family type etc. However, the number of EVs was negligible at the time, and the availability of only smart meter data for the purpose of the analysis did not allow the derivation of any relevant conclusions. Indeed, the sole use of smart meter data is not sufficient to fully describe EV charging behavior because important characteristics cannot be derived (e.g., differentiating between plug-in and start of charging or extracting EV plug-out times).

The work of [9] calculated load coincidence factors of sets of EVs based on the size of a population, charger installed power and vehicles battery size. Due to the lack of real and updated data, the authors calculated coincidence factors for Denmark using a mix of transport survey data for traveled distances and arrival times, together with charging data from the US collected between 2015 and 2016 from 24 kWh Nissan LEAFs. Ref. [10] analyzes the impact of residential EV charging on three low voltage distribution grids in Copenhagen, Denmark. While the authors use real household and network data, they resort to the use of an agent-based simulator (GAIA) with input from the Danish National Travel Survey to generate the required EV data.

Study [11] focuses on a dataset of residential EV users belonging to Trondheim, Norway. Again, the size of the dataset is small, containing a total of 6878 charging sessions for 55 vehicles spanning from December 2018 to January 2020, providing information about plug-in/out times and charged energy. The authors outlined the differences in charging behavior for level 1 and level 2 charging modes, concluding that users with higher charging power have more potential for demand-side flexibility. A study case from Sweden is analyzed in [12] and uses residential EV data of 159000 sessions from 855 chargers between Nov. 2020 and Oct. 2021. The main goal of the study is to assess the hosting capacity of a real distribution grid. The dataset comprises only plug-in/out times and charged energy values, limiting the comprehensive examination of EV charging patterns. Additionally, the one-year duration of the dataset precludes drawing conclusive insights into periodic effects and trends, particularly in the post-COVID era.

Ref. [13] provides valuable insight into the driving and charging habits of a diverse population in the UK. The article summarizes findings from a large EV trial running in the UK from 2013 through 2015. While detailed data was recorded, the trial had a rather experimental nature where all participants were given a Nissan LEAF to operate. Data from a successor trial in the U.K., the *Electric Nation* project, is used in [14]. The authors analyzed real residential EV data from 265 unique users from years 2016–2018 and created a stochastic agent-based model to generate EV load curves. Focus is primarily given on the plug-in behavior of the users, and the authors stress the importance of non-systematic behavior, i.e., users do not plug-in their vehicles daily. Based on the developed model the authors study the impact of plug-in behavior on system integration studies and primarily on coincidence factors. However, again there is no differentiation between plug-in and start of charging and the analysis does not clarify if users adjust their behavior based on prices; analyses on aggregated load are done based on hypothetical uncontrolled vs price-responsive modes.

A much larger and more extensive dataset of 3.2 million charging events in the U.K. from 2017 [15] has been used and analyzed in various works, e.g., [16], but can be considered rather outdated due to recent technological developments, while it spans only one year. An analysis of 2018 data from 26000 EVs in Beijing, China, was presented in [17]. The extensive data availability and the large number of analyzed vehicles provide a robust statistical representation. However, the charging and plug-in times are not differentiated, implying that no form of smart charging is applied and vehicles charge immediately upon connection. In [18], the authors used data from one major charging station provider containing nearly 6 million sessions from 119 thousand drivers in California in 2019. However, only 0.5 million sessions correspond to residential users while data from a single year is used. The study implements load shifting/modulation but mainly addresses scalability issues of scheduling algorithms, without a detailed analysis of charging behavior.

In [19] the authors used real charging data of 74 residential and not-residential charging locations in Saskatchewan, Canada, from April to October 2021 to create aggregated charging profiles. The data is very detailed and includes information about charging power and locations, driving times, charging time interval, EV model, start charging time, and the initial/final SOC. However, due to the short duration of the dataset (only one month is analyzed in the paper) and the relatively small number of EVs included, drawing any conclusions becomes challenging.

1.2. Contributions and organization

The presented literature review revealed the gap in up-to-date empirical investigations of EV charging behavior. Most of the presented data is outdated, while many studies rely on information from small populations, often under an experimental setup or from synthesized data using various sources due to the lack of actual charging data from EVs and chargers [20]. Consequently, any resulting power profiles (often in the form of coincidence factors) are often not realistic, while smart charging impact is usually simulated assuming certain degrees of controllability.

This paper aims to fill the aforementioned gaps with the following contributions. First, a thorough and detailed data analysis of 5534 chargers is conducted based on an extensive EV charging data from Denmark, covering a period between September 2021 until December 2023. Various important characteristics are presented that describe EV charging behavior in the wake of COVID-19 and the energy crisis of 2021–2022. Second, given the ability of users to perform delayed charging by postponing the power-start time, a unique analysis on EV user delayed charging behavior (which can be seen as a form of manual smart charging) is performed and discussed. Third, real aggregated consumption patterns of EVs are presented and compared with standardized profiles from the literature, showing the impact of

Table 1
Description of the parameters extracted from raw data.

Parameter	Explanation
$t_{\text{plug-in}}$	Timestamp of plug-in time
$t_{\text{plug-out}}$	Timestamp of plug-out time
t_{start}	Timestamp of start of charging process
t_{end}	Timestamp of end of charging process
ΔT_{delay}	Duration of delay
ΔT_{charge}	Duration of charging
$\Delta T_{\text{session}}$	Duration of session
e	Charged energy during the session
P	Max power during the session

user-induced charging delay and the need for empirical data to capture real behavior and trends.

The rest of the paper is structured as follows. Section 2 describes the dataset used in this study and provides some background information. Section 3 presents a thorough analysis of all main EV charging characteristics. Section 4 conducts an analysis of the impact of delayed charging behavior on daily load profiles and compares them with standardized profiles from the literature. Section 5 concludes the paper.

2. Dataset description

The analyzed dataset includes charging sessions occurring between September 2021 and December 2023 from a set of 5534 residential charging stations which are installed and operated by the Danish e-mobility platform provider (eMPP) Spirii. Customers are equipped with the 22 kW AC charger *Zaptec Go* [21]. However, most residential installations in Denmark are equipped with a 25 A fuse which allows for a maximum of 11 kW 3-phase charging. Using higher charging power, if this is allowed by the onboard charger, would restrict non-EV household consumption and load management techniques for load sharing would be needed, which are not yet common.

A complicating factor in our analysis is that multiple EVs may have been connected to each charger at some point in time (a preliminary investigation suggests that at least 10% of the customers own two vehicles). Further, each vehicle's model, onboard charger power and battery capacity are unknown, as vehicle-specific information is not communicated. The chargers are installed over a wide geographic area throughout Denmark. The company's portfolio has been continuously expanding, and the total number of installed residential chargers increases by approximately 200 per month. To guarantee a sufficient number of sessions per charger, only those installed prior to May 2023 are analyzed. After a data filtering process to remove erroneous data, a total of 1.3 million sessions remained.

Each charger communicates with the eMPP and transmits data that contains timestamps with the power and energy meter values at a frequency of typically 60 s. A charging session is initiated when the user plugs in the vehicle, resulting in an entry with a timestamp $t_{\text{plug-in}}$. The user has the option to start charging immediately or to postpone the process via an app. By analyzing the raw data it is possible to identify the user-induced delay ΔT_{delay} by comparing t_{start}, i.e., the point when power starts to be drawn, with $t_{\text{plug-in}}$. It is also possible to identify the point in time t_{end} when charging power becomes zero. A signal is also sent when the user unplugs the vehicle, leading to an entry with a timestamp $t_{\text{plug-out}}$. The derived information is graphically depicted in Fig. 2.

The charged energy e that includes losses is recorded for each session but the exact amount of energy flowing in the vehicle's battery (i.e., after losses) is unknown. Finally, from the power values recorded at each timestamp the maximum value P can be calculated, which is considered as the charging capacity of the session. The aforementioned parameters are summarized in Table 1. The charging utilization rate is defined as the ratio of the charge duration divided by the duration of the session [22]:

$$UR = \frac{\Delta T_{\text{charge}}}{\Delta T_{\text{session}}}. \quad (1)$$

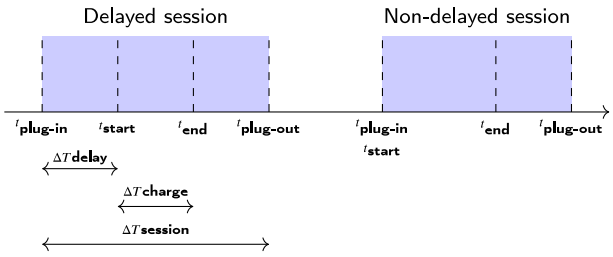

Fig. 2. Parameters related to charging sessions data.

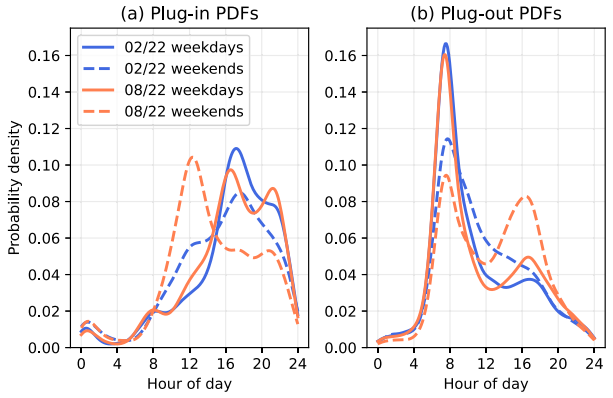

Fig. 3. KDE of the PDFs of plug-in (subplot (a)) and plug-out times (subplot (b)) for two selected months.

3. Data analysis

3.1. Plug-in and plug-out times

Two key characteristics of EV charging behavior are plug-in and plug-out time. It is common in the literature to refer to plug-in as arrival time, though those events are in general different; the same holds for and plug-out and departure time. This distinction is important for residential chargers and it must be noted that plug-in/out times are typically the ones that are available. Kernel density estimation (KDE) is used to visualize the underlying data distribution with respect to hour of day (in local time). Our analysis reveals the difference in plug-in and plug-out time distributions between weekdays and weekends and across months. The probability density functions (PDFs) are shown in Fig. 3 for two selected months.

Notice how the distributions of plug-in time (subplot (a)) are similar during weekdays for Feb. 2022 and Aug. 2022, indicating work-related commuting activity with a peak around hour 17. However, while weekdays and weekends in February exhibit a similar pattern, in August the peak moves towards 11 during weekends, indicating more outdoor activity. The PDFs of plug-out time (subplot (b)) are also similar between the two months during weekdays, with a peak between 7–8. However, weekend PDFs exhibit a different behavior with density shifting from morning to later hours, especially during the summer month.

These results indicate seasonal and weekly patterns in plug-in and plug-out times. They also necessitate the use of more detailed representation of these characteristics compared to lumped distributions. The evolution of the four distributions for each month of the dataset is shown in the Appendix in the form of ridgeline plots. A small seasonal effect can be observed in the plug-in times of weekdays with the density of the distributions concentrating around the afternoon during autumn/winter months, then increasing in density in later hours during spring/summer. Weekends have a stronger seasonality with peaks shifting from the evening in winter/autumn to late morning hours

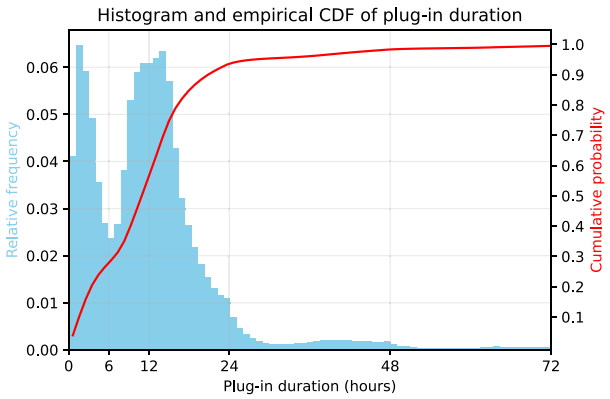

Fig. 4. Histogram and corresponding empirical CDF of the plug-in duration of all charging sessions.

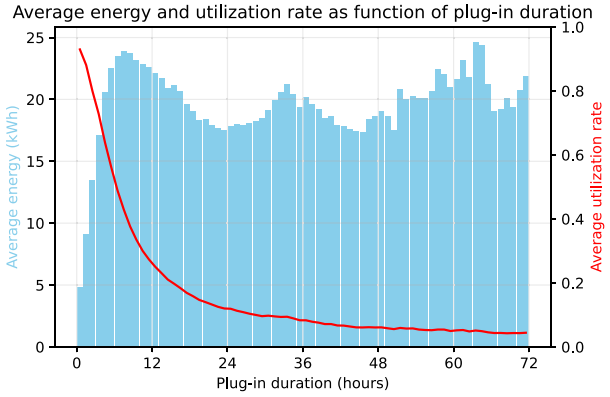

Fig. 5. Average energy and charging utilization rate as a function of plug-in duration.

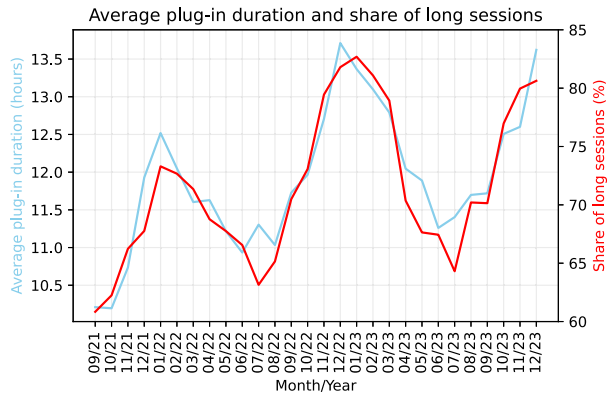

Fig. 6. Evolution of the average plug-in duration and the share of charging sessions lasting more than 6 h.

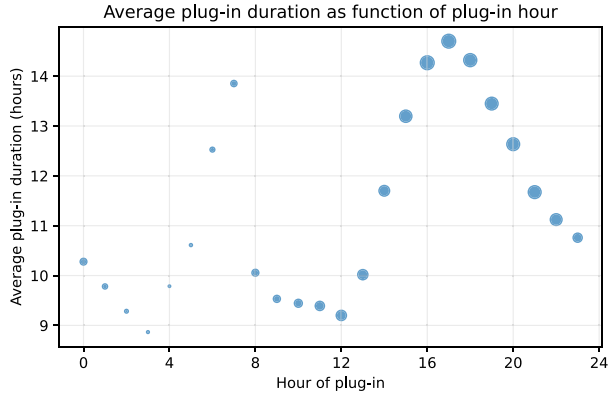

Fig. 7. Average plug-in duration as a function of plug-in hour. Circle size indicates the frequency of the sessions.

in spring/summer. Plug-out times show a more consistent behavior, especially during weekdays, where the peak always occurs around 7. Again, some seasonality is observed in weekends, where a second peak around hour 16 appears during spring/summer months. This is probably related to more outdoor activity.

3.2. Plug-in duration

Fig. 4 shows the histogram and the corresponding cumulative distribution function (CDF) of the plug-in duration in hours. Two regions of high probability density emerge: one corresponds to short sessions lasting only a few hours and another to mostly overnight charging of approximately 12 h. In the sequel we will use this 6-hour threshold to distinguish *short* from *long* sessions for convenience. 35% of the sessions last between 9 and 15 h, and most typically correspond to overnight charging, while only 8% of the sessions last more than 24 h.

Fig. 5 shows the average energy and utilization rate as a function of plug-in duration. On average 5 kWh are charged for sessions lasting less than one hour, with this value increasing linearly by 4 kWh/hour until a duration of 6 h. After that the average energy presents some variation around a mean value of 20 kWh. As expected, the average utilization rate for short sessions is much higher and the charged energy lower, indicating little room for flexible charging. The utilization rate drops rapidly to less than 0.5 for a plug-in duration of 6 h, indicating a larger potential for load shifting of long sessions. The rather small average energy of 5 kWh despite the high utilization rate of 0.9 for 1 h sessions is attributed to the presence of very short sessions (e.g., below 30 min) and the existence of EVs with low onboard charging power capacity (3.7 kW). The reported value of 5 kWh covers the whole dataset, but this value increases from below 4 kWh in late 2021 to more than 5 kWh in late 2023, indicating that the average onboard power capacity of the portfolio increases over time.

The evolution of the average plug-in duration and share of long sessions is shown in Fig. 6. 2021 and early 2022 are likely affected by COVID restrictions which could have had a significant effect on commuting and user behavior. Excluding this period, there are no year-to-year significant variations. However, a seasonality is observed for both parameters, where they increase significantly during winter months and drop during the summer. This phenomenon coincides with reduced outdoor activity during winter months.

The average plug-in duration as a function of plug-in hour is shown in Fig. 7. Few sessions start between 0–6, while the majority correspond to a plug-in time of 15–23. As expected, a sinusoidal-like pattern shows that users who plug in later leave their EV plugged for a shorter time period. This behavior matches well with work-related commuting, where users who plug in their EV around 16 will plug out on average 14 h later (around 6) to commute to work.

3.3. Charged energy

The histogram of the charged energy per session and the corresponding CDF are shown in Fig. 8. Energy sessions require 0–80 kWh, with approximately 50% of them having a consumption of less than 12 kWh. The histogram demonstrates a high density of energy values below 12 kWh, followed by a nearly constant linear reduction. This behavior can be partially attributed to the presence of PHEVs, whose battery capacity is lower, but also to frequent BEV charging. Fig. 9 shows the average session energy for each plug-in hour of

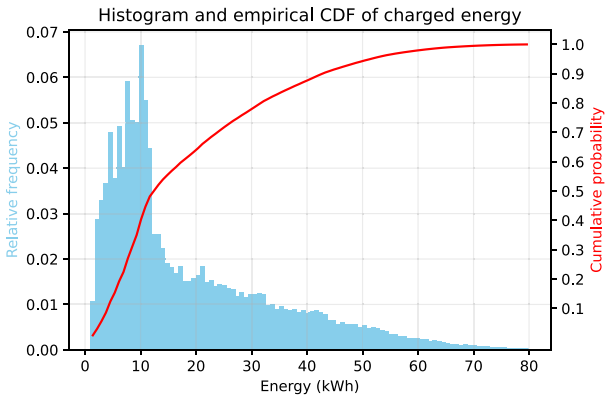

Fig. 8. Histogram of the charged energy per session and the corresponding empirical CDF.

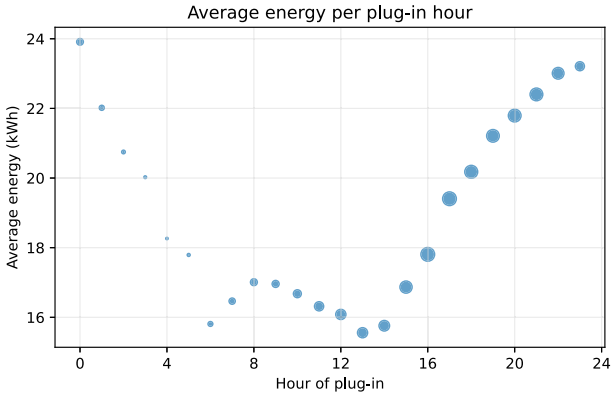

Fig. 9. Average energy per session for each plug-in hour of the day. Circle size indicates session frequency.

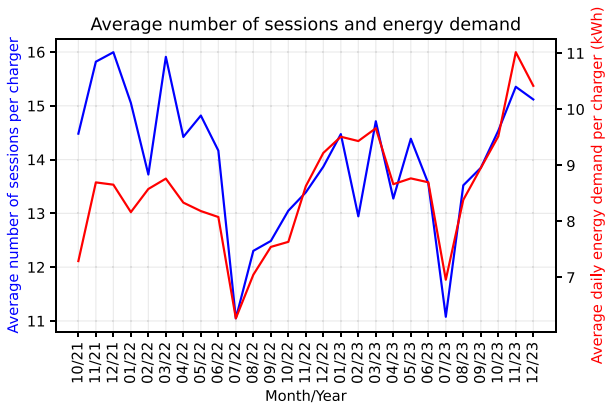

Fig. 10. Evolution of the average number of sessions per charger (left axis) and average daily energy demand per charger (right axis) for each month of the available dataset (excluding the incomplete September 2021).

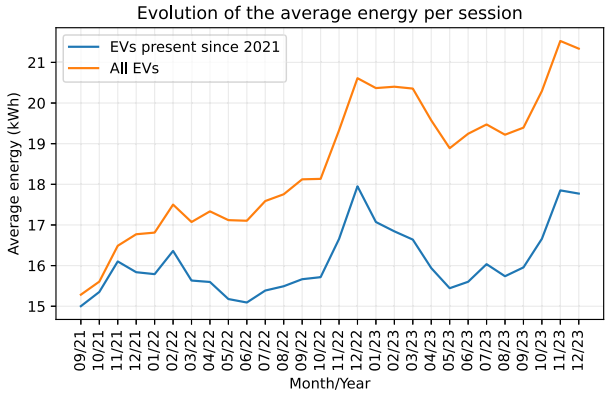

Fig. 11. Evolution of the average energy per session for each month of the available dataset for EVs present since 2021 and for all EVs in the expanding portfolio.

the day. Interestingly, energy values increase as users plug-in their vehicle after 15, which can be partially attributed to longer commuting times/distances.

Fig. 10 shows the evolution of the average number of sessions per charger in blue, where no noticeable trend is observed. The average daily energy demand for each month is shown in red, where a small increasing trend of around 1 kWh on a year-to-year basis is shown, probably due to increased commuting during the post COVID-19 period and higher shares of BEVs. There is a notable seasonal effect with fewer sessions and less energy demand during the summer, probably as a result of more holidays, less work-related commuting and higher ambient temperatures (and thus EV efficiency). The average energy per session for all EVs in the portfolio and for a subset of EVs present since 2021 is shown in Fig. 11. Excluding the irregular post-COVID period of late 2021/early 2022, the average energy per session shows a seasonal effect with values increasing in the winter period and decreasing in the summer period. A small upward trend is observed, which increases when the whole portfolio is considered, most likely due to the growing percentage of BEVs in the portfolio.

3.4. Re-plug period

Fig. 12 shows the histogram of re-plug period, which is defined as the time duration between the plug-in time of two consecutive charging sessions, together with the corresponding average energy demand. A large density peak occurs at 24 h, revealing a recurrent pattern of commuting and users who plug-in their vehicle every day. The histogram has pronounced peaks at multiples of 24 h, indicating that users plug-in periodically every few days at roughly the same time. Regarding the corresponding use of energy, the larger the time difference between two sessions' plug-in time, the larger the charged energy, likely due to longer driven distances in the meantime. However, the rate of increase in demand gradually decreases and saturates after 4 days. 40% of the sessions are fewer than 24 h apart, 70% fewer than 48 h apart and 85% 72 h apart. A notable exception in the increasing trend is the higher average energy values for consecutive charging sessions within one hour or less, which have a relatively large average power of 18 kWh. This could indicate the presence of a second EV or a failed/disrupted preceding session.

3.5. Use of delay function

EV users have the option of postponing the power-start time to decrease energy costs. Due to technical and communication issues power-start is not the same as plug-in time even if there is no user-induced delay. For this reason, we classify a charging session as delayed if the delay is larger than 15 min. Fig. 13 shows the evolution of the delayed sessions' share along with that of prices.

A year-to-year comparison suggests an increasing trend which coincides with a spike in electricity prices in Aug. 2022. This indicates that high electricity prices increased awareness and led to an increase of the delay utilization rate above 50%. Fig. 13 also suggests a seasonal variation of the use of delayed charging with reduced values during summer months and an increase during the winter. This can be partially

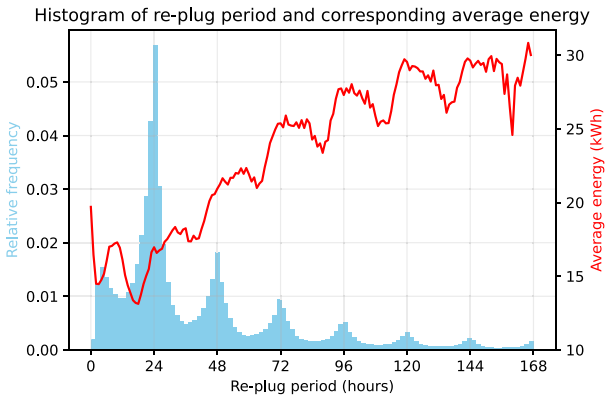

Fig. 12. Histogram of the re-plug period and the corresponding average energy demand.

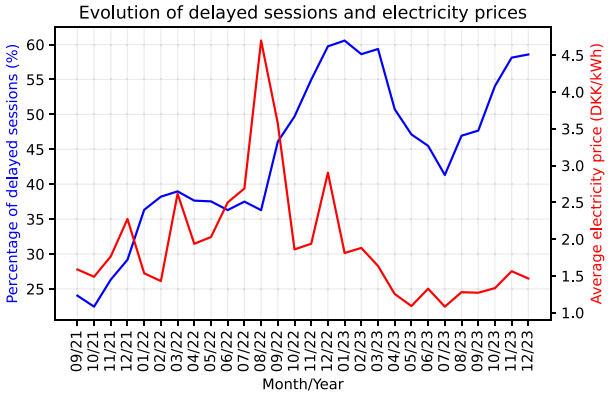

Fig. 13. Evolution of the share of delayed sessions and the average total electricity price excluding taxes. Note: residential EV owners currently do not pay electricity tax in Denmark.

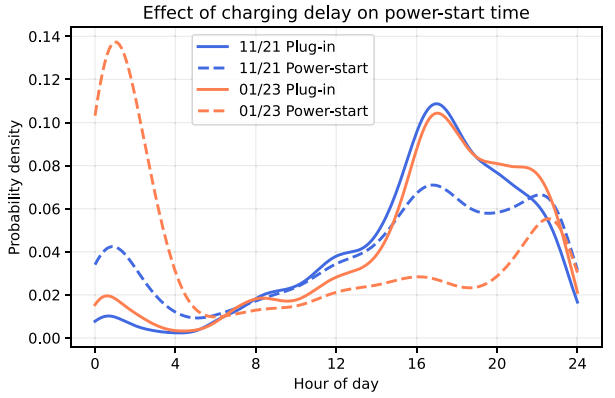

Fig. 14. KDE of the PDFs of plug-in and power-start times for two selected months.

explained by the larger shares of short sessions (see Fig. 6) and reduced energy needs during the summer.

Fig. 14 shows the PDF of power-start and plug-in times for Nov. 2021 and Jan. 2023. While the plug-in time distributions do not change over two months, this is not the case for the power-start distributions. A shift of the latter towards later hours (after 20) is already seen in Nov. 2021, but in Jan. 2023 the shift is much more prominent, with the majority of sessions postponed between 22 and 2. The evolution of the power-start times PDF is presented in the Appendix in Fig. 24. A gradual shift towards 0–2 can be seen, along with a seasonal increase

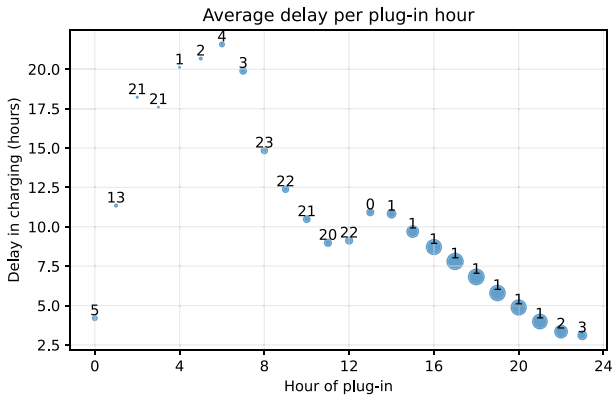

Fig. 15. Average user delay as a function of plug-in time. Circle size indicates the frequency of charging events; the top number shows the average power-start time due to the delay.

of density towards noon in the summer, which moves to later hours during the winter.

The average delay time as a function of plug-in time is shown in Fig. 15, along with the corresponding average power-start time. For those calculations only sessions which were delayed were accounted for, i.e., sessions with a delay longer than 15 min. The later users plug-in their EV, the shorter the delay is. This leads to most sessions being, on average, postponed to hour 1. Naturally, this leads to significant power peaks during that time of the day.

Most users apply delays that postpone charging after 22 and usually around 1. This can be explained by the lower spot prices during those hours and the avoidance of the high DSO tariff during the evening peak of 17–21. Given the rather low spot price variability and low (and constant) DSO tariff between 0–6, users do not seem to pay particular attention to the exact time of lowest spot price, but rather simply delay charging to hours of typically low spot prices and early enough to guarantee full charging, especially for PHEVs. This simple strategy proves particularly effective in capturing most of the economic benefit that is possible through delayed charging.

4. Power profiles analysis

4.1. Spirii dataset

In this section we provide charger load patterns under the use of delayed charging and we show how these change over time. Chargers are continuously added to the portfolio and for this reason power is divided by the number of active chargers at each month. This normalization is necessary to remove the trend introduced by the continuously added chargers in the portfolio and to express consumption as kW per charger. Unlike [9], we do not use coincidence factors to present our results. The first reason is that some chargers are used by multiple vehicles which have different charging capacities. The second is that a charger's maximum power is not constant and is affected by various factors such as SOC, voltage, reactive power etc. Finally, the vehicles' onboard charger capacity is unknown. As a result, a coincidence factor would be insufficient to obtain load values in kW, as chargers typically consume either 3.7 kW or 11 kW. Presenting normalized results as kW per charging point is more insightful, especially for grid planning purposes. In the following we refer to April until September as the summer season and October until March as the winter season.

The average charger occupancy (i.e., how many of the chargers have an EV connected) for each hour–month is shown in Fig. 16. The occupancy rate in weekdays varies from around 10% during midday to 30%–40% during the night in 2023. A notable exception is July, which is expected as it is the summer holiday period in Denmark. The

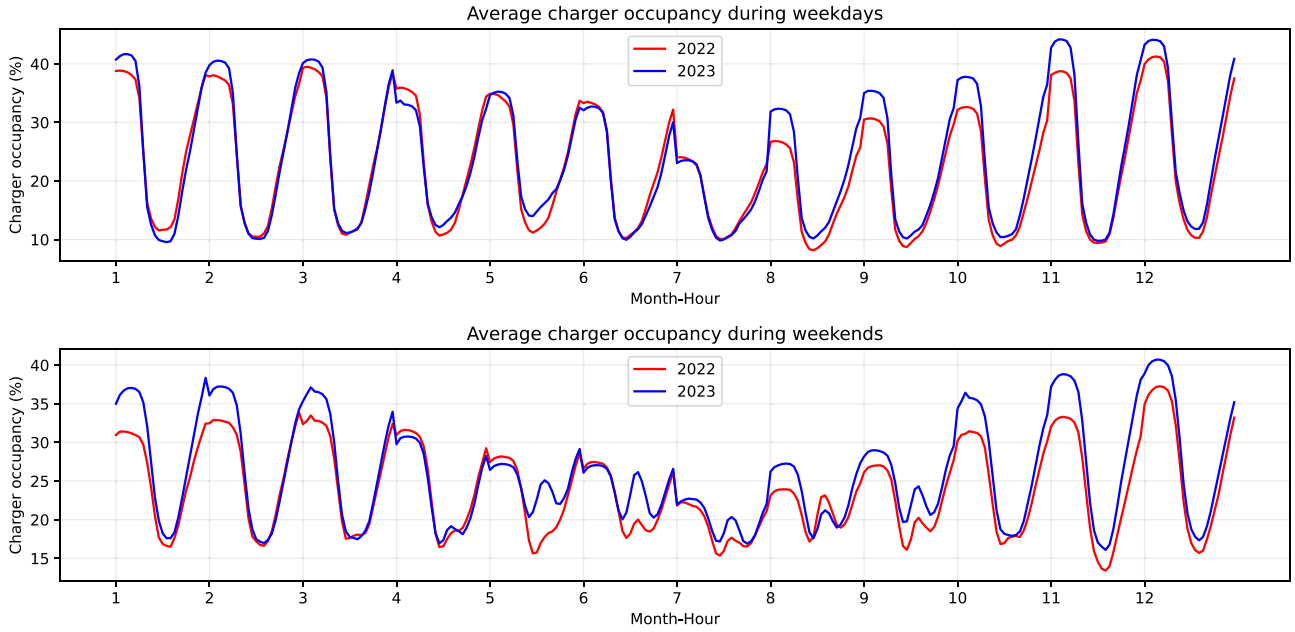

Fig. 16. Average occupancy rate of the chargers during weekdays (top plot) and weekends (bottom plot).

pattern is similar between the two years but the rate increased by a few percentage points in 2023 during August–December. Weekends present a similar pattern to weekdays during the summer season, though with a smaller variation between day and night; again, the rate increased by a few percentage points in 2023. Occupancy rates have a different pattern in weekends during the summer season. Occupancy has a smaller variation throughout the day and is noticeably lower compared to the winter season, probably due to more outdoor activity/traveling.

Next, the average load per charger for each month–hour (similar to [23]) is presented in Fig. 17. In 2023, consumption during weekdays was mainly concentrated during night hours (from 23 to 2), with very low average load of 0.1–0.25 kW/charger during the rest of the day. On average, consumption became more concentrated in the first semester of 2023 compared to that of 2022, possibly due to the extensive use of delayed charging. The impact of the effect of delayed charging seems to stabilize in the second semester, as the average load pattern between 2022 and 2023 is similar. However, the average load during the night increased year-to-year by approximately 0.2–0.5 kW/charger during the winter. A seasonal variation is evident, with the average load dropping in the summer season and presenting lower variability throughout the day. The reduction in power values was already suggested by the smaller monthly energy consumption shown in Fig. 10. The average load in weekends has a pattern that is similar to that of weekdays for the winter season. The situation is different in the summer season, where the average load presents two peaks, one larger during noon and a smaller during midnight. This behavior is driven by charger occupancy and prices, since those are typically lower during those hours in summer months due to larger solar production and low consumption.

Fig. 18 shows the maximum loading per charger for each hour and month. The patterns are similar to those of the average values during weekdays. However, the maximum values are considerably higher, reaching 2.5 kW/charger in the winter season of 2023, a marked increase by 1 kW per charger compared to 2022. It should be noted that a larger year-to-year increase in the maximum load occurs in the first months of 2023 compared to 2022, while the changes are smaller towards the end of the years. Similar results can be seen during weekends, where the patterns are similar to the average values but the maximum loading increases by 0.5–1 kW/charger from 2022 to 2023 in the first three months. Interestingly, the differences in the maximum values are less significant in the later months of the two years. This can be attributed to the increased use of delayed charging after the surge in electricity prices in the summer of 2022 (see also Fig. 13).

These results show the significance of user behavior and technological developments on EV consumption profiles, and the importance of using evidence from real data. An overall increase in the average and maximum loading per charger is observed, with notable seasonal and weekly effects. The impact of the more intense use of delayed charging that led to more concentrated charging during the night and higher peaks is seen from the winter season of 2022, and the effect in winter season 2023 is weaker. It will be interesting to examine whether these trends will also be observed in 2024 and if these loading values will saturate.

4.2. Comparison with profiles used by DSOs

In 2021 Dansk Energi (now Green Power Denmark) published standardized electricity consumption profiles for a variety of loads (houses, heat pumps, etc.), among which were residential EV profiles [24]. Green Power Denmark is a non-commercial business organization representing 1500 members from across the green energy value chain. The published EV profiles were constructed not through smart meter or charging data, but by combining various data sources. Two different types of profiles were derived: flexible ones, where load was distributed throughout the day, and profiles assuming immediate charging upon user arrival at home. The daily median profile for weekdays for three different cases is presented in Fig. 19: immediate and flexible charging based on the median values calculated in the report [24], and measured values from the presented dataset for 2023.

The measured daily median profile shows the effect of price-responsive charging with markedly higher load values between 0–4 and much lower values for the rest of the day. The standard profiles present a very different picture. Immediate charging leads on average to a high peak during the evening and zero load between 0–8, based on the assumption that users arrive mostly around 2–5 and immediately start charging their EVs. However, the presented analysis showed that a large number of EV users employ the delay functionality and an *immediate* (usually also called *dumb* in the literature) average profile as the one shown in Fig. 19 is unrealistic. The terms *smart* and *flexible* charging are often used in the literature but their interpretation is

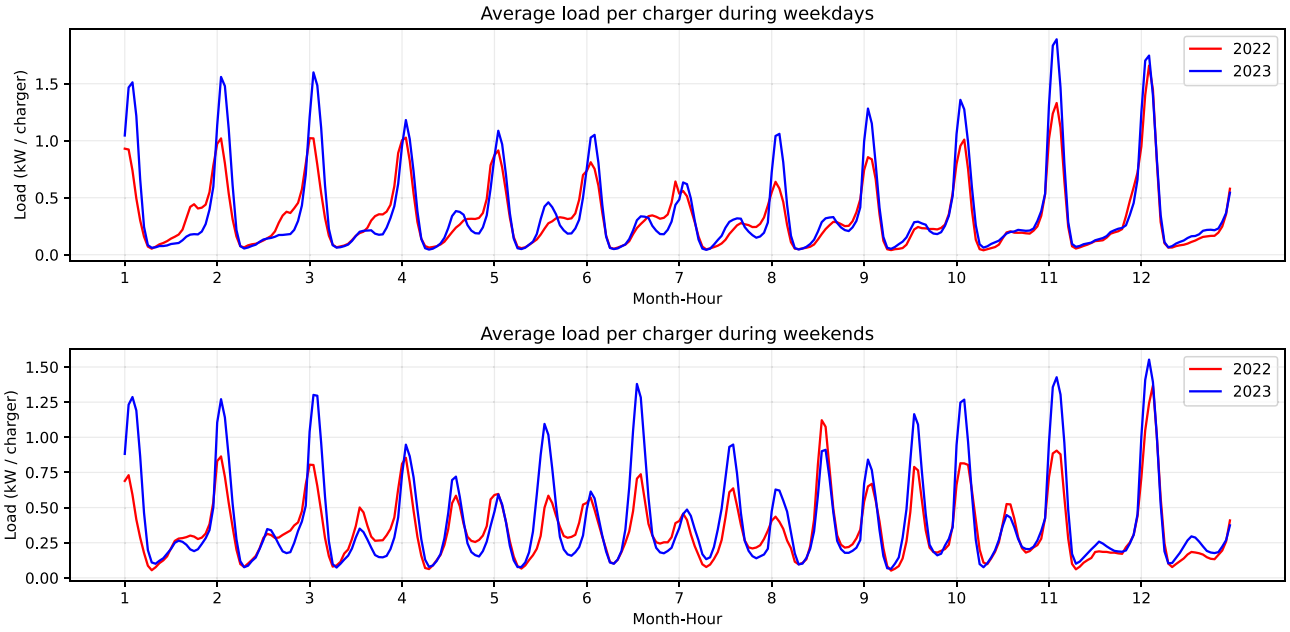

Fig. 17. Average load per charger during weekdays (top plot) and weekends (bottom plot) for each month–hour.

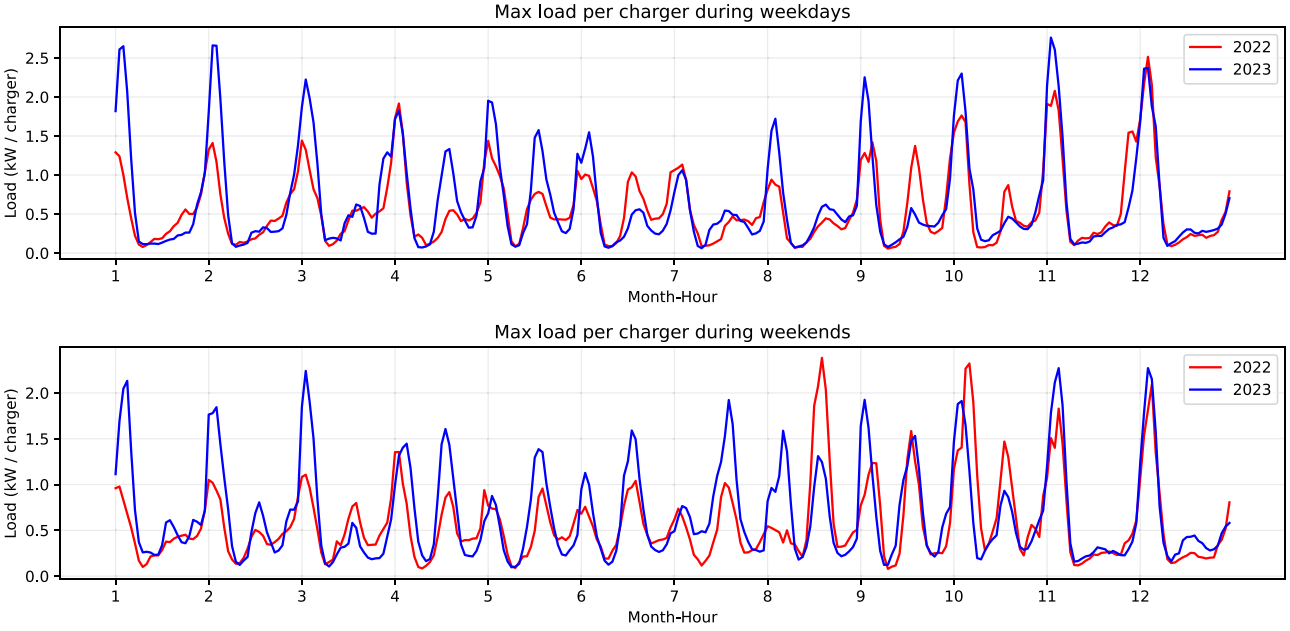

Fig. 18. Max load per charger during weekdays (top plot) and weekends (bottom plot) for each month–hour.

often subject to the relevant context. Therefore, the flexible profile from [24] is very flat and presents an ideal load distribution for a DSO. Charger occupancy rates and user plug-out times suggest that such load flattening is to some extent unrealistic. In contrast, real-world evidence suggests that delayed charging (if that can be referred to as *smart* or *flexible*) leads to high peaks concentrated around the low price period of 0–4.

Report [24] recognizes the lack of real-world charging data and is also based on probably outdated sources, facts that highlight the importance of using real and up-to-date empirical evidence for studying EV charging behavior. The high peaks that occur as a result of implicit user coordination could result in excessive loading in distribution networks, calling for a load-flattening strategy to achieve an average profile closer to the one presented in the report. The current frameworks, pricing mechanisms and business models incentivize users to take advantage of the lowest prices, leading to pronounced peaks over few hours of the day.

5. Conclusion

In this work a thorough analysis of up-to-date Danish residential EV charging data was presented. Various interesting aspects of user behavior and how these evolve over time were discussed. By using

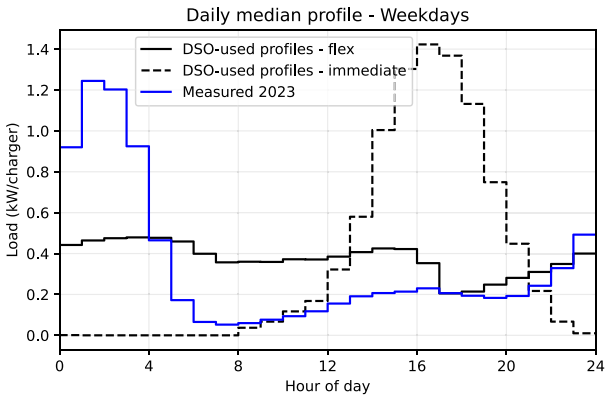

Fig. 19. Daily median profile for weekdays for four different cases: immediate and flexible charging [24], and measured from the presented dataset for 2023.

recent data from ordinary users a realistic depiction of user behavior and its effect on EV consumption can be made.

Our analysis shows the periodicity and evolution of various charging characteristics. One of the key results is that charging sessions become on average longer and with higher energy needs, and the share of long-lasting sessions increases. However, these parameters, along with the use of the charging delay functionality, show a strong seasonal effect with lower values during the summer season and higher during the winter season for all four parameters. The increase of the average session energy is largely attributed to the growing shares of BEVs, and not in changes in the charging behavior of existing users. The resulting higher charger occupancy and average energy per session increase the opportunities for flexible scheduling of EV demand, especially in cases on 11 kW onboard chargers. This potential is higher during the winter.

A unique feature of this study is the investigation of manual demand response in EV charging. Our analysis shows the increasing use of this functionality and the result it has on average and maximum loading per charger. Delayed charging leads to rather short in duration peaks during early morning hours, which could potentially result in congestion under a high EV penetration scenario. Interestingly, summer peaks during weekends shift to midday hours as a result of low prices and higher charger occupancy. The maximum loading per charger is still rather low, but it shows a significant increase from 1.25 kW/charger in early 2022 to 2.5 kW in early 2023. It should be noted that the changes in charging behavior and EV loading were greater during winter 2022, and the year-to-year difference with 2023 was less significant. The aforementioned changes in EV charging behavior and the impact they have on EV loading show the importance of up-to-date investigations using real data to have a realistic representation of EV as electrical loads in power system studies.

In our future work we are planning to carry out a detailed comparison between EV user behavior in Denmark and other countries, to understand how the various characteristics analyzed in this work differ. Further, we will attempt to unravel the key drivers behind EV user behavior, such as weather/price/time dependencies, and understand how this behavior evolves over time as users gain more experience. Our end goal is to create appropriate models that can be used to infer and forecast charging behavior and consumption.

CRediT authorship contribution statement

Charalampos Ziras: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Malthe Thingvad:** Visualization, Methodology, Investigation, Data curation. **Torben Fog:** Resources, Project administration, Funding acquisition. **Ghaffar Yousefi:** Writing – original draft, Investigation, Data curation. **Tilman Weckesser:** Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization, Project administration, Supervision, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share the raw data, but the data needed to reproduce the figures are provided in [25].

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Appendix

Figs. 20–24 present the evolution of the distribution of plug-in, plug-out and power-start times over 2022 and 2023.

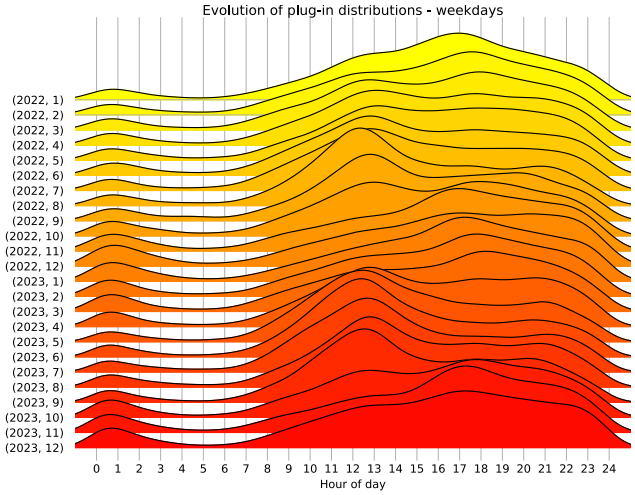

Fig. 20. The evolution of the PDF of plug-in times during weekdays for each month in the available dataset.

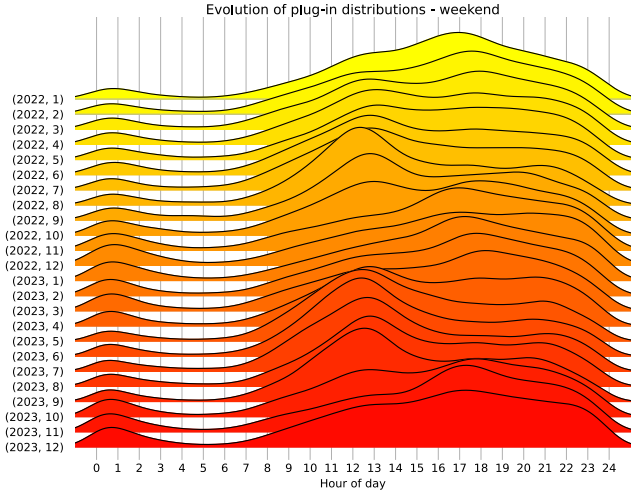

Fig. 21. The evolution of the PDF of plug-in times during weekends for each month in the available dataset.

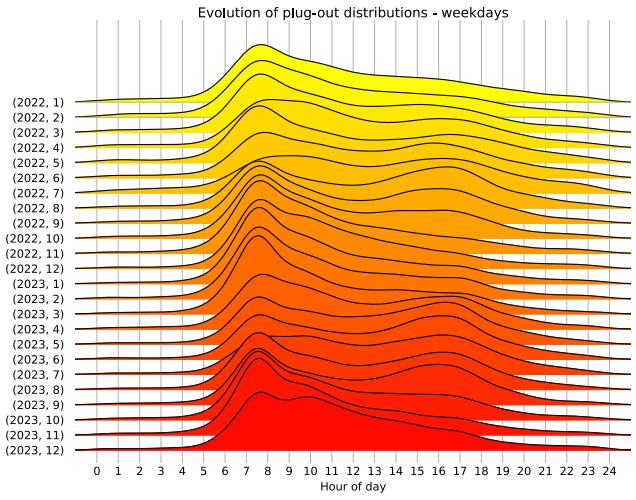

Fig. 22. The evolution of the PDF of plug-out times during weekdays for each month in the available dataset.

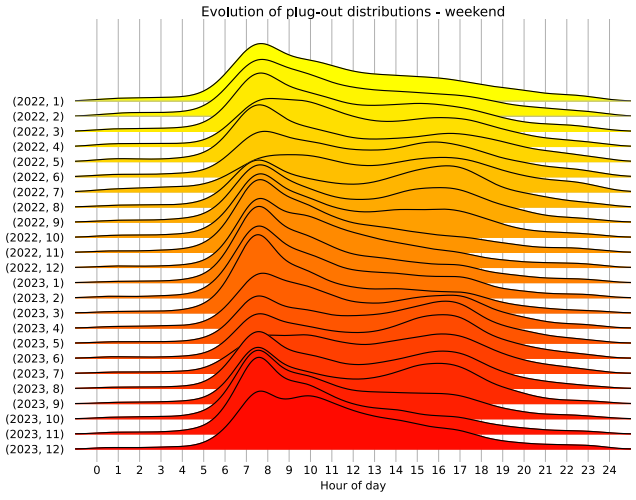

Fig. 23. The evolution of the PDF of plug-out times during weekends for each month in the available dataset.

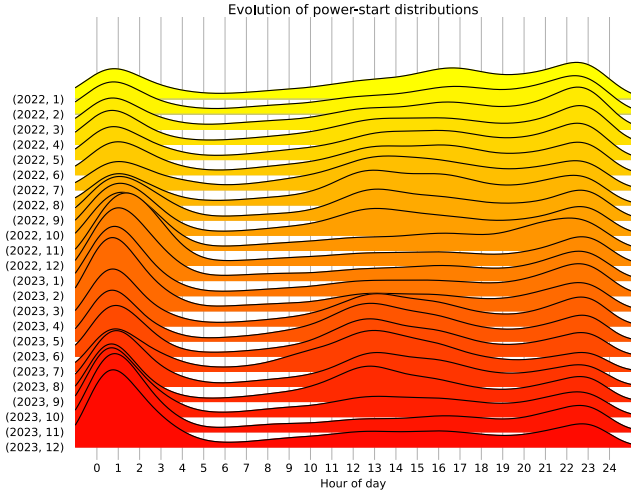

Fig. 24. The evolution of the PDF of power-start times for each month in the available dataset.

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