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RESEARCH ARTICLE

# Statistical Characterization of Public AC EV Chargers in the U.K.

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**ABSTRACT** In recent years, the public AC electric vehicle (EV) charging network in the United Kingdom (UK) has experienced significant growth, more than doubling in size. However, there remains a significant lack of information regarding usage patterns, which hampers decision-making for future infrastructure planning. This study addresses this gap by presenting a statistical analysis based on data from nearly twelve thousand EV charging sessions. The data was collected from 595 AC charging sockets, with 85% operating at 7 kW and the remaining 15% at 22 kW, throughout the UK between April 2022 and July 2022. The analysis focuses on key factors that define the primary characteristics of the current public EV charging ecosystem, including utilisation rates, arrival-departure times, sojourn durations, energy transfer, and overstay durations. Several important observations are made, such as the variability in utilisation rates, factors influencing overstay periods, and peak demand periods. With two case studies, the potential role of smart charging in leveraging EV flexibility is shown by lowering and shifting the peak EV loads. The findings of this study have significant implications for the planning and efficient allocation of investments to expand the charging infrastructure. By gaining a better understanding of the current charging ecosystem, informed decisions can be made to optimise the usage and expansion of EV charging facilities.

**INDEX TERMS** Electric vehicles, AC charging, statistical analysis, smart charging, overstay.

## I. INTRODUCTION

There has been an emphasis on the move towards electric vehicles (EVs) as a means of decarbonising the road transport sector. This sector generates nearly one-fourth of the global greenhouse gas emissions [1]. In parallel, regional EV markets are expanding at a faster pace driven by subsidies and policies that will see a ban on the sale of new petrol and diesel cars within a decade (e.g., UK, France, and Germany [2]). The EV market is also driven by falling lithium-ion battery costs and improvements in battery technology that supports longer all electric range [3]. EV sales are passing key tipping points in various major economies. In the US, EV sales have surpassed 5% of new vehicle sales [4]. In the UK, EV sales represented nearly 17% of all sales in 2022, exceeding the sales of new diesel cars for the first time [5]. According to Statista Research [6], EV sales (both battery and plug-in hybrid) are expected to reach 16 million per year by 2027 and the resulting market volume is projected to reach 858 billion USD by the same year. In Table 1, global EV market and annual sales are presented.

Despite achieving multiple milestones in both of these areas, a number of studies have shown a perceived lack of public infrastructure and gaps in end-user education in different parts of society [7]. Previous research indicates that domestic (off-street) charging is highly relevant for early adopters; however, it is not attainable for driver groups living in buildings with multiple occupancy (e.g., flats or tenements) who rely on public infrastructure [8], [9]. Therefore, with no immediate change in the incumbent building stock

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**TABLE 1.** Global electric vehicle and charging station market analysis (2016-27) [6].

| | Collected Data | | | | | | | Projection | |
|---|---|---|---|---|---|---|---|---|---|
| in thousands | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2025 | 2027 |
| Battery Electric Vehicles | 477.7 | 801.6 | 1367.8 | 1624.6 | 2165.4 | 4599.4 | 5211.8 | 9274.8 | 13325.9 |
| Plug-in Hybrid Electric Vehicles | 283.8 | 405.3 | 624.7 | 561.5 | 968.8 | 1908.5 | 1913.0 | 2464.8 | 2881.0 |
| Total (BEV, PHEV) (by 2022) | | | | | | | **22914.1** | | |
| Charging Station | 215.3 | 309.7 | 371.7 | 587.2 | 809.0 | 1210.3 | 1430.3 | 2251.6 | 2799.5 |

anticipated, the need for accessing public charging stations will be more important over the next decade. In Table 1, global charging station installation statistics are provided for all charger types. It is noted that the pace of EV sales is significantly higher than the installation rates of charging stations. This results from charger deployments requiring a number of steps to be completed prior to installation (i.e., grid connection application, siting permissions), leading to significantly longer times. This issue is reported in California, where a sizeable portion of EV owners switch back to petrol vehicles as the pace of charging infrastructure expansion cannot keep up with the EV adoption rates and provide the coverage and capacity needed [10].

Nowadays, most public chargers are operated by private businesses. Therefore, the economics of charging stations, which are determined by utilisation rates, usage characteristics, and potential queuing times, need to be carefully investigated. The economics of charging stations further depend on charging types: AC (7 kW (single phase) and 22 kW (three-phase), DC (50 kW and above), and associated infrastructure investments. For instance, the required investments increase exponentially for deploying fast DC chargers due to the high upfront cost associated with complex power electronics components and associated protection equipment, along with civil works required to bring a 3-phase electricity connection to the site [11]. Hence, fast DC chargers require higher utilisation rates to be profitable [4], [12]. According to [4], fast DC charging is expected to be profitable after 2025 due to low utilisation rates. For Level 2 or 7 kW AC chargers, amortizing the investments is more achievable as the capital investments are significantly lower than DC chargers, and grid reinforcements are less urgent.

Over the next decade, significant investments will be made to deploy charging infrastructures at scale. The success of such investments requires data-driven analysis of the current charging network. To this end, it is critical to statistically model and characterize EV charger usage patterns to understand current usage patterns, utilisation rates, and peak consumption hours, and in doing so, inform decision-making. The contributions of this paper can be listed as follows:

- We conduct a statistical analysis of nearly twelve thousand charging sessions from 595 public AC chargers (7 kW and 22 kW) in the UK, specifically between April and July 2022.
- By utilizing machine learning-based clustering methods, we characterize EV charging behavior based on the times of arrival and departure, allowing us to identify distinct behavioral clusters.
- We systematically analyze key charging behaviors, such as utilisation rates, arrival times, sojourn durations, and overstay durations (instances when the vehicle remains plugged in but not actively charging). We conduct these analyses separately for weekends, weekdays, and different charger types.
- To understand the factors influencing overstay periods, we develop a metamodel based on response surface methodology, taking into account factors such as charging cost and arrival time.
- We present two case studies to show how smart charging can be used to exploit EV flexibility (due to overstay periods) to reduce and shift EV charging demand.

To the best of the authors' knowledge, this is the first study conducted for the UK and will fill a critical research gap by presenting a statistical analysis of public AC chargers in the UK market. UK and will fill a critical research gap by presenting statistical analysis of public AC chargers in the UK market.

The rest of this paper is organized as follows: In the next chapter, a detailed literature analysis is presented. In Section III, the dataset and its attributes are described. In Section IV, statistical analysis for charger utilisation, session clustering, arrival-departure analysis, sojourn durations, and energy transfer is presented. In Section V, analysis for overstay is investigated, which involves a metamodel and a case study with smart charging. The last section provides conclusions, discussions, and limitations of this study.

## II. LITERATURE REVIEW

There has been a growing body of literature on data analysis and statistical modeling of EV charging sessions for different countries/regions. In [13] and [14], 390k charging session data collected from public chargers in the Netherlands between 2011-15 are analyzed. Using the DBSCAN algorithm, first, the data is clustered into three distinct clusters (park to charge (62.8%), charger near home (27.8%), and charge near work (9.4%)) based on arrival and departure hours. In the dataset considered in this paper, a similar clustering analysis is carried out. In this case, however, the data is dominated by a single cluster (daytime charging 82%) as the dataset does not contain records from work and home charging chargers. When the determined empirical probability density functions are compared with violin plots of "charge near home" and "charger near work" datasets, both analyses show two peak charging periods (morning and afternoon). Similar to our study, authors also analyzed sojourn and idle times to quantify the smart charging potential. In the literature, various terms (idle, overstay, charge idling) are being used to show the amount of time an EV is plugged and not charging. In this paper, these events are referred to using the term *overstay*, which is a growing concern at the moment for charge point operators.

Overstay analysis is presented in a number of studies [4], [15], [16]. In [4], the overstay durations are presented as a percentage of sojourn durations for different locations. It is reported that for Level 2 (6.6 kW chargers), the overstay percentages are 49%, 30%, 61%, 50%, 76%, 37%, 44%, and 51% for office, retail, municipal, medical, parking lot, leisure, transit, and hotel venues, respectively. When DC fast charging is compared, these values are all less than 11% for the same venues. In [15], the EV charging station capacity problem with overstaying customers is studied. In the proposed model, the station is assumed to operate under heavy traffic, and overstaying EVs are interchanged with waiting customers to increase EV charger utilisation. The model is applied to real-world data collected from parking lots in San Diego, CA. It is reported that while the mean charging duration is 2 hours, 90% of the drivers tend to overstay for 75% of their sojourn duration. In [16], overstay durations are aimed to be shaved by pricing schemes to induce human behavior and reduce station congestion. In operational fast charging applications, the overstay issue is tackled through myopic prices such that a fee is charged after a short grace period. For example, the pricing tariff for Tesla Superchargers is 1 USD/min when the station is fully occupied [17].

Additionally, a study conducted in Canada [18] analyzed approximately 7,000 charging events. The results revealed that the median number of charges per 7 kW AC charger was 0.4, and the median energy transferred during each charging event was 6.6 kWh. Another study conducted in Western Australia [19] examined the usage of both AC and DC chargers. The analysis demonstrated that the number of charges per day for both AC and DC chargers was lower than 0.4. Additionally, the study found that similar to our findings, a significant portion of charging sessions were extended beyond the required duration. These extended periods accounted for nearly half of the overall charging duration. In a separate analysis presented in [20], data from fast DC chargers in the UK and USA were analyzed. Another study conducted on a major US university campus during the early years of EV adoption (2011-13) [21] focused on statistical analysis of EV charging events. The study revealed that the extended periods of charging sessions were considerably higher during that time period, indicating a similar trend to our findings. This was attributed to the availability of free parking provided to EVs at that time.

In [22], the statistical charging analysis of 19,617 charging sessions of 17 EVs at 19 chargers (level 1, 2, and 3) at the University of California Los Angeles campus is analyzed. The findings obtained from EV charging events indicate that 90% of these events involved a transfer of less than 12 kWh. In terms of the duration of EV plug-in time, it was observed that 67% of the time, EVs were connected for less than 4 hours, while 87% of the time, EV users plugged in their vehicles for less than 7 hours. In [23], domestic EV charging and the application of smart charging were examined. This study further investigates how EV charging impacts the power systems by examining peak demand. The paper encompasses six different use cases, each involving different optimization signals and incentives for drivers. The results of the study indicate that these optimization techniques are successful in redistributing the charging load from periods of high grid costs and congestion, particularly during the early evening, to times of lower grid costs, such as the early morning and midday. The study reveals that approximately 15-20% of charging was shifted away from specific hours, while 20-30% of charging was shifted into specific hours, showcasing the effectiveness of the most impactful use cases. In [24], a predictive methodology, based on demographic data, is developed to understand the utilisation of chargers (domestic, work, public). It is concluded that most drivers would prefer to charge at home, while only 1.7% of the drivers would prefer to use a public AC charger.

Over the last decade, there has been a well-established literature on the impacts of electric vehicle charging on power grids, which is documented in several review papers [25], [26], [27]. The impact studies can be grouped into two categories. The first group focuses on power quality and asset impacts, such as harmonics, voltage levels, phase unbalances, and transformer aging, resulting from EV charging at the distribution level. For additional perspectives, the studies discussed in [28] and [29] specifically investigate instances of thermal limit violations and voltage dips that occur when multiple EVs are charging. On the other hand, reference [30] demonstrates that with a 50% EV penetration rate (half of the households owning EVs), substantial infrastructure upgrades would be necessary to accommodate the increased demand for EV charging. Furthermore, reference [31] examines the impact of EV charging on a distribution transformer serving six households. The results of high-resolution simulations indicate that if households begin to adopt multiple EVs, the local transformer may become overloaded. To address negative impacts, smart charging frameworks and/or storage-based solutions are considered [32].

The second group of studies focuses on the impacts of EV charging on peak electricity generation for a specific region or country. Probabilistic methods, such as Monte Carlo simulations and agent-based modeling, are often employed to account for various parameters, including charging times, charger types, EV demand, and vehicle types [33], [34]. The aforementioned studies often assume a high penetration of EVs and drivers following certain statistical behaviors based on time-of-use surveys. Consequently, the results of this study can be used to provide more realistic assumptions regarding public EV charging behaviors, such as charging demand, arrival, and departure times.

Statistical analysis of public chargers plays a crucial role in modeling and forecasting the increase in EV adoption rates resulting from investments in EV infrastructure. [35] demonstrates that establishing a charging infrastructure can lead to a 200% increase in EV ownership rate in rural Norway over a five-year period. Similarly, [36] shows that greater access to home charging reduces the reliance on public charging. This aligns with our own findings presented in later sections, where we highlight low utilisation rates (less than 5%) due to a high percentage of customers utilizing home charging.

## III. DATASET

This paper utilizes data obtained from a prominent charge point operator's network in the United Kingdom, consisting of both 7 kW and 22 kW chargers. The dataset encompasses approximately twelve thousand charging sessions conducted between April 1, 2022, and July 31, 2022, throughout the UK. It is important to note that the majority of chargers are situated outdoors, except for a small percentage located in multi-storey car parks. Furthermore, no significant weather events occurred during this period. Specifically, the minimum temperatures recorded in the UK during April, May, June, and July were 3.5, 7.8, 9.3, and 11.8 degrees Celsius, respectively. Similarly, the maximum temperatures recorded during these months were 12.6, 15.9, 18.6, and 21.3 degrees Celsius [37]. Therefore, weather conditions did not affect customer demand. The charge point network consists of 370 unique charge points, each comprising one or more charging sockets. Among these, there are 505 7 kW charging sockets and 90 22 kW rapid charger sockets. These chargers are deployed across various locations in the UK, with a total of 156 different addresses, including major cities such as London, Glasgow, York, and Birmingham. The overall geographical distribution of the chargers is illustrated in Figure 1.

### A. DATASET ATTRIBUTES

For each charging session the dataset includes the following parameters:

- A unique *Session ID* is assigned for each session.
- *Charging Power* is either 7 or 22 kW as described above.
- *Session Start Date and Time* shows when the vehicle is plugged-in.
- *Session Stop Date and Time* shows when the vehicle leaves the charger.
- *Duration* attribute shows the total duration the vehicle spends as plugged in.
- The amount of energy data is reflected via *Total Energy* attribute (in kWh).


FIGURE 1. Location of chargers in the UK.

It is noted that the data for *Duration* are less than or equal to the total charging duration, as the vast majority of vehicles *overstay* after completion of charging.

## IV. EV CHARGING DEMAND ANALYSIS

This section presents the probabilistic analysis of EV charging demand across the charging network. As a start, the number of daily charging events from April 1, 2022 until July 31, 2022 is presented. It is highlighted that not all chargers were active since the beginning of the study, hence active charger numbers are also presented in Figure 2. It can be seen that the charging network has almost doubled in three months and daily charge events have significantly increased in line with this.

### A. CHARGER UTILISATION

To better analyse EV charging habits, the charger utilisation rates are analysed. A utilisation rate $u_i$ of an arbitrary charger $i$, takes values between 0% and 100%, is defined as

$$u_i = \frac{\sum_j D_j}{T_i}, \tag{1}$$

where $D_j$ is the duration of EV $j$ connected to charge $i$ and $T_i$ is the total duration of when charger $i$ is operational. All $D_j$ and $T_i$ values are obtained from the data set and are converted into hours. The utilisation rates for 7 kW and 22 kW chargers are further differentiated because rapid chargers have shorter

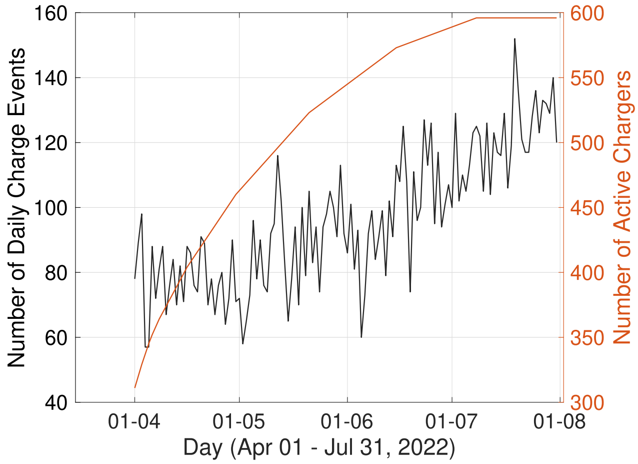


**FIGURE 2.** Number of daily chargings across the charging network.

**TABLE 2.** Twelve-month utilisation rates (%) of AC chargers (7 and 22 kW) across Europe (source: [38]) and 2.5 years data for the USA (source: [4]). UK data is four months.

| Finland | Sweden | Denmark | Norway | Switzerland | USA | UK |
|---|---|---|---|---|---|---|
| 6 | 8 | 9 | 9 | 7 | 3.5 | 5 |

charging sessions. Box plots for utilisation rates are presented in Figure 3. From this figure, the following results are obtained. The mean and median utilisation rates are 4.78% and 2.2% for 7 kW chargers, respectively. While these are 4.38% and 4.15% for 22 kW chargers. Note that in industry practice, the first 90 days of a charger are often considered as the "get to know" period and chargers which are operational for less than 90 days are not taken into account. Next, the chargers which are operational for less than 90 days are removed and the utilisation rates are calculated as follows. The mean and median utilisation rates increase to 5% and 4.85%, respectively for 7 kW chargers and to 4.45% and 2.56%, respectively for 22 kW chargers. In Table 2, utilisation rates of AC (<22 kW) chargers are presented. The data for five countries are collected from 12 thousand charging stations for 12 months (see [38]). Comparing our results with other countries given in Table 2 with high EV sales is critical to understand driver charging behavior in public charging places based on different demographics and regions. For instance, in Finland, access to a dedicated charger rate is lower than the UK [39] and this is reflected as higher usage of AC chargers. Similarly, the public DC charging is highly utilised when compared to AC charging in the US [4]. Such findings could provide useful insights for the UK case when people in different demographics purchase EVs (e.g. no dedicated charging). At the moment, it can be seen that UK utilisation rates, based on four months data, are slightly lower than European counterparts and higher than the US average.

The results for number of charging sessions per charger per day are presented in Figure 4. The median values are 0.12 and 1.39 for 7 kW and 22 kW, respectively. In [4],

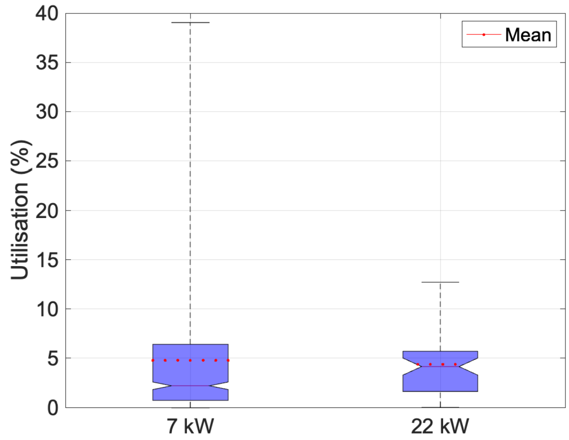


**FIGURE 3.** Utilisation rates for chargers. The bottom and top of each box are the first (25th percentile) and third quartiles (75th percentile) of charger utilisation. The distance between the bottom and top of each box is the interquartile range. The red line in the middle of each box is the median (second quartile or 50th percentile), while the dotted redline shows the mean value.

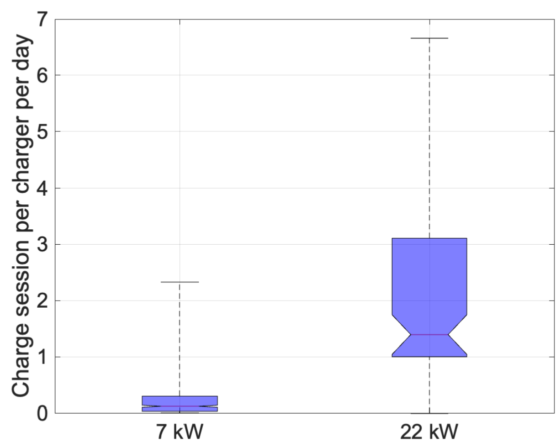


**FIGURE 4.** Number of chargings per charger per day.

a similar analysis is presented for a charging network in the US, and it is reported that the number of charging per charger per day is 0.42 for Level 2 chargers (equivalent to 7 kW chargers) and 0.69 for fast DC chargers (50 kW). One of the primary reasons for low utilisation rates is the fact that most of the early adopters in the UK have access to private garage or driveway (urban (72%), town/fringe (72%), and rural areas (93%)) as reported from a recent survey [40]. Detailed analysis of charging habits of EV drivers in the UK are presented in Table 3 (based on 1002 respondents). It can be seen that only 8% of the EV owners use public charger once or more than once a day. As a direct consequence, public chargers are underutilised.

### B. SESSION CLUSTERING

In this section, we analyse the charging sessions to study driver behaviour in terms of arrival and departure times. Note

**TABLE 3.** **Frequency of EV owners charging away from home in the UK [40].**

| Charging Frequency | Percentage |
|---|---|
| Less often than once a month | 26% |
| Once a month | 10% |
| Once a fortnight | 5% |
| Once a week | 12% |
| 2-3 days a week | 10% |
| 4-6 days a week | 8% |
| Once a day | 7% |
| More than once a day | 1% |
| N/A | 20% |

that a charging session has three parameters:

$$\textit{Sojourn session} \triangleq \delta_{sojourn} = t_{departure} - t_{arrival} \tag{2}$$

$$\textit{Charging session} \triangleq \delta_{charging} = t_{charging-end} - t_{arrival} \tag{3}$$

$$\textit{Overstay} \triangleq \delta_{overstay} = \delta_{sojourn} - \delta_{charging} \tag{4}$$

Sojourn times given in (2) are directly calculated from our dataset using *Session Start* ($t_{arrival}$) and *Stop* times (($t_{departure}$). Duration of charging sessions, given in (3), are estimated by assuming that an EV starts charging as soon as it is connected to a charger. Then, charging duration is calculated by dividing the *Total Energy* attribute by the rated power of the charger (7 or 22 kW). An overstay period, given in (4), is calculated by subtracting the corresponding charging session from the corresponding sojourn duration. Note that this approach has limitations because, due to efficiency losses and additional limitations of on-board chargers, the actual charging rate could be lower than the rated power. Therefore, actual charging sessions could be slightly longer than our calculations. Nevertheless, the proposed methodology could easily be adjusted if instantaneous power data is accessed and more accurate results can be calculated.

In order to examine the temporal characteristics of sojourn durations, we cluster sojourn sessions by arrival and departure times. In the field of Machine Learning, there are variety of clustering algorithms which are differentiated based on the approach to process the data (partitioning, hierarchy, density, and distribution, see entire list [41]). In related literature [13], [14], DBSCAN (density-based clustering algorithm) is used to cluster EV arrival-departure times. DBSCAN can identify arbitrary shape and size clusters without specifying the number of clusters as opposed to k-means or G-means clustering algorithms. Moreover, DBSCAN is well suited to tackle irregularly shaped clusters and outliers which are caused by long parking durations. Therefore, DBSCAN is employed to cluster arrival-departure patterns.

The DBSCAN algorithm assigns an arrival-departure pair to a cluster (e.g. day-time charging) if it is in proximity to many other points in that cluster. The algorithm takes two input parameters: $\epsilon$ (eps), which specifies the radius of the region, and minPts, which indicates the minimum number of points needed to create a dense area. The DBSCAN algorithm works as follows: Initially, $D$ random points are chosen from the dataset. All the points within the $\epsilon$ radius of the selected points are considered core points. The number of core points grows as more points are added until a border condition is met. Border points are those with at least one core point within their $\epsilon$ radius, but do not have the minimum number of minPts to extend the cluster. These border points serve as the boundaries of the cluster. Any points that are not core or border points are classified as noise. The disadvantage of DBSCAN is its high sensitivity to the input parameters ($\epsilon$, minPts). Therefore, input parameters are empirically obtained from the dataset ($\epsilon = 1.4$, minPts=60;).

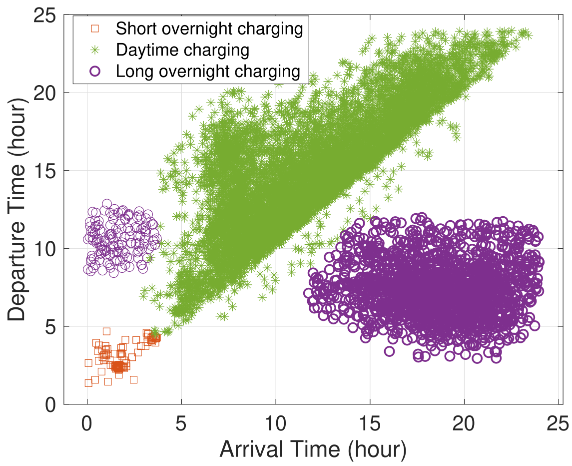


**FIGURE 5.** **Session clustering of EV charging sessions. Three clusters have been identified: short overnight (0.9%), daytime charging (82%), and long overnight charging (17.1%).**

In Figure 5, the result of the DBSCAN algorithm is presented. Three different clusters are identified: 0.9% of sessions are short overnight charging, 82% of sessions are daytime charging, and 17.1% of sessions have long overnight charging. This is mainly because most charge points do not allow long parking as they are located in public locations. Moreover, compared to study presented in [13], the dataset considered in this paper contains less "park to charge" or "charge at work" sessions both of which takes 10+ hours. Since sessions clusters are dominated by daytime charging, the rest of our analysis is applied to all dataset rather than specific clusters.

### C. ARRIVAL-DEPARTURE ANALYSIS

Statistical analysis of EVs' arrival and departure processes to a charger is critical to understand overall EV demand profiling and designing larger-scale charging systems. The arrival process is often probabilistic in nature and refers to key parameters such as time distribution of EV arrivals and statistical behaviour of inter-arrival times. Departure process is related to the duration of time a vehicle is connected to a charger, hence refers to statistical distribution of a "server" becoming available. It is noteworthy that EVs are not always charged during the time they are connected, and *overstay* analysis will be discussed in the next section.

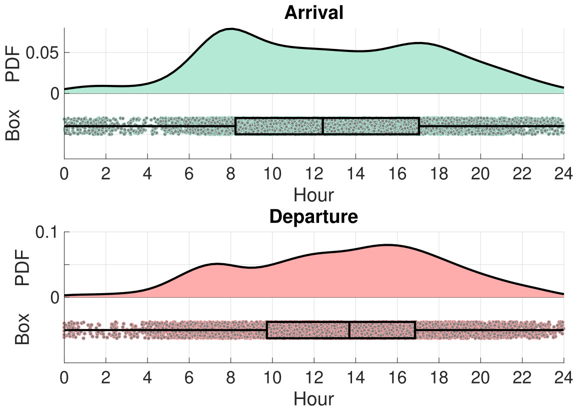


FIGURE 6. Arrival and departure analysis for weekday and 7 kW chargers.

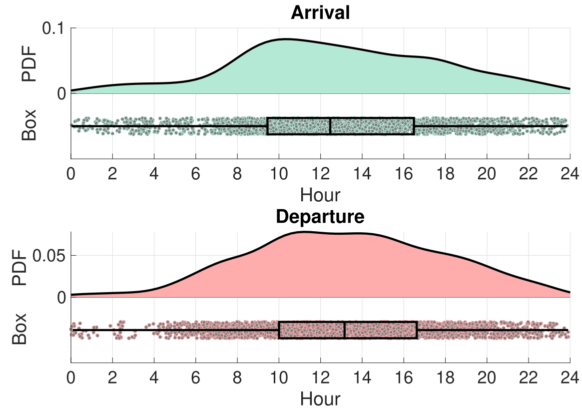


FIGURE 7. Arrival and departure analysis for weekend and 7 kW chargers.

Arrival and departure times are examined based on charger type (7 kW and 22 kW) and weekday/weekend due to differences in their respective charging behaviours. For all cases, the analyses are presented in a raincloud plots which combine probability density functions (PDF), jittered raw data, and box plot [42]. In Figure 6, analysis for weekday and 7kW charging network are presented. It can be seen that there are two peak periods during the day around 8 am and 5:15 pm, potentially representing commute to and from work or school. The arrival density between the two peaks is fairly uniform, and half of the arrivals occur between 8:15 pm and 5 pm. Departure behaviour is different from the arrival as most of the plugged-in vehicles leave in the afternoon with a peak departure time of 15:45 pm. There is also a visible departure peak in the morning around 6:30 am, representing overnight chargings.

In Figure 7, the analysis discussed above is extended for weekends (7 kW chargers). It can be seen that the charger usage characteristics change. There is a single peak hour around 10 am, while half of the arrivals occur between 9:15 am and 4:45 pm. Departures, on the other hand, have the highest density between 10 am and 2:45 pm. The number of departures between 12 am and 4 am is significantly lower when compared to weekday, indicating tendency for long overnight charging.

Our analysis is extended for 22 kW chargers and results are presented in Figures 8 and 9. It can be seen that the daytime charger access characteristics is similar to 7 kW charger case. However, box plots show that the amount of overnight charging (11 pm to 6 am) is very low when compared to 7 kW chargers as the charging session is shorter.

In literature ([43], [44]), charging stations with multiple sockets are often modelled as a queuing system. In such cases, the distribution of inter arrival times and service durations determine the type of queue (e.g. Markovian queues) and associated performance metrics (e.g. waiting times etc.). For instance, the literature predominantly assumes that inter arrival times of EVs follow an exponential distribution. This is mainly because the exponential distribution has mathematically tractable properties which enables us to obtain closed form expressions for station parameters. On the other hand, to model a charging station with a queue model, the inter arrival times should be relatively short. Otherwise, the station operator would not experience issues related to congestion and queuing. Therefore, inter arrival times data longer than 60 minutes are filtered and distribution fitting is applied.

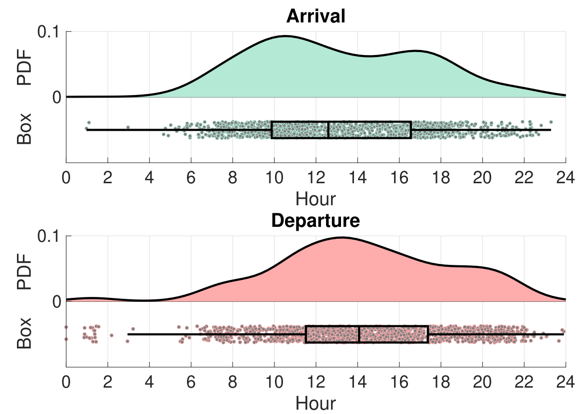


FIGURE 8. Arrival and departure analysis for weekday and 22 kW chargers.

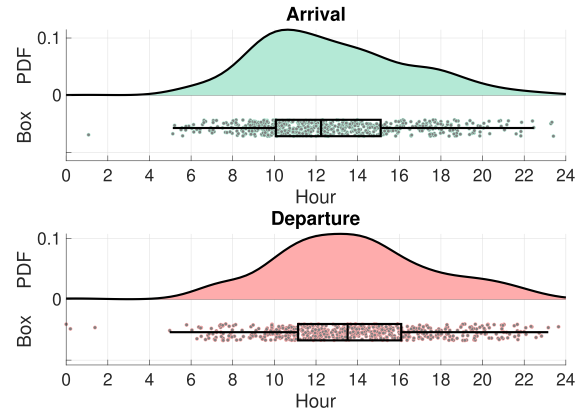


FIGURE 9. Arrival and departure analysis for weekend and 22 kW chargers.

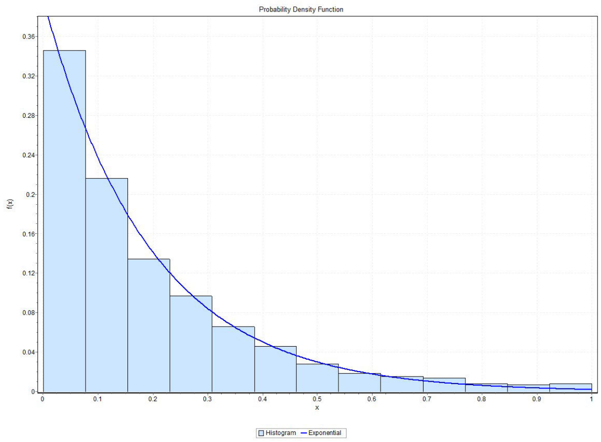


**FIGURE 10.** Distribution fitting of inter arrival times (0-45 minutes).

In Figure 10, the results are presented for maximum inter arrival durations of 45 minutes. It can be seen that exponential inter arrival times assumption is reasonable acceptable given high accuracy in fitting. A goodness of fit is carried out using Chi-Squared test which provides a measure of how far the observations are from the expected data. This is calculated by

$$\chi^2 = \sum\left(\frac{Observed - Expected}{Expected}\right), \tag{5}$$

where the sum is over all possible values. The Chi-square ($\chi^2$) statistic value is 14.4 and p-value is 0.27. Moreover, the $\lambda$ parameter is 5.7 meaning that average inter arrival time is $1/\lambda = 18$ minutes. Note that $\lambda$ denotes the mean of Exponential distribution.

In Table 4, a more detailed analysis is presented for three different inter arrival intervals. It can be seen that for up to 30 and 60 minutes intervals, the best distributions are Weibull and General Gamma. In this table, the best distribution and the exponential distribution cases are presented and compared.

### D. SOJOURN DURATIONS

This section presents the analysis for sojourn duration which is defined in (2). The raincloud plots for 7 kW and 22 kW chargers are presented in Figures 11 and 12. For 7 kW chargers, the results show that EVs stay connected to a charger longer in weekdays than weekends. The primary reason is the fact that weekday driving distances are higher than weekends, thereby the energy needs change accordingly [46]. Figure 11 also shows that there are more overnight charging events on weekdays than weekends. This can also be observed from the quartiles. On weekdays, the first, the second, and the third quartiles are 2.05, 3.95, and 8.82 hours, respectively, while 25% of the sojourn durations are higher than 8.82 hours. On weekends, these quartiles are 1.4, 2.8, and 7.4 hours, indicating a noticeable reduction.

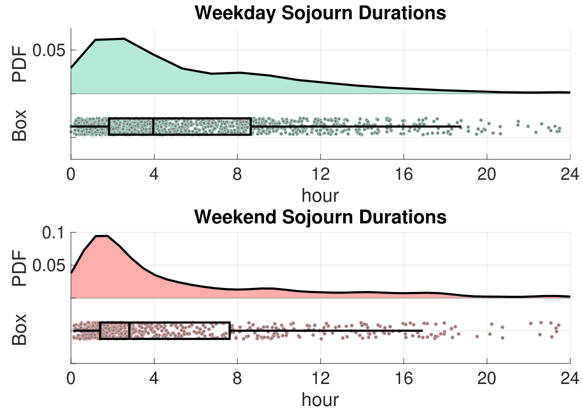


**FIGURE 11.** Sojourn durations for 7 kW chargers.

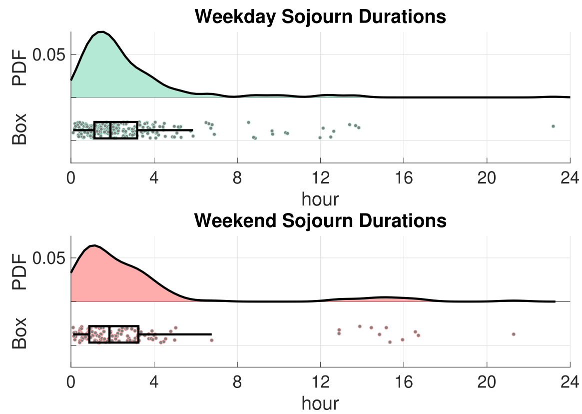


**FIGURE 12.** Sojourn durations for 22 kW chargers.

The sojourn times for 22 kW chargers are significantly shorter than 7 kW chargers due to higher power rating. For weekdays, the first three quartiles are 1.3, 1.9, and 3.1 hours, while weekend sojourn times are, in parallel to 7 kW charger case, shorter, and the first three quartile values are 0.89, 1.8, and 3.1 hours, respectively. These values are critical in designing charging stations and quantifying their impacts on the power grid.

### E. ENERGY TRANSFER

The statistical analysis of energy transfer (in kWh) per charging session is a critical to understand potential impacts of EVs on grid and predicting local peaks. Our analysis is carried for weekend and weekdays and for both charger types. The results for 7 kW chargers are presented in Figure 13. It can be seen that for weekdays, first, second, and third quartiles are 7.04 kWh, 12.44 kWh, and 26.1 kWh, respectively. The results for weekend analysis is similar and first, second, and third quartiles are 6.96 kWh, 11.68 kWh, and 24 kWh, respectively. Due to privacy policy, we do not have access to vehicle types, initial and final state of charge levels. Nevertheless, with the increasing capacity of electric vehicle (EV) batteries (30+ kWh), a significant portion of charging sessions (approximately 75% of all sessions) corresponds to

**TABLE 4.** Fitted distribution for various inter arrival times. $\lambda$ is the mean of Exponential distribution. $\alpha$ and $\beta$ denote statistical distribution parameters for Weibull and Gamma distributions [45].

| | Exponential Distribution | | | Best Distribution | | |
|---|---|---|---|---|---|---|
| Inter arrival Duration (min) | Parameter | $\chi^2$-Statistic | p-value | Parameter | $\chi^2$-Statistic | p-value |
| 0-30 | $\lambda$=6.7 | 38.5 | 0.001 | Weibull ($\alpha$=1.04, $\beta$ = 0.155) | 26.713 | 0.0085 |
| 0-45 | $\lambda$=5.7 | 14.44 | 0.27 | Exponential ($\lambda$=5.7) | 14.44 | 0.27 |
| 0-60 | $\lambda$=5.18 | 20.13 | 0.064 | Gen. Gamma (k=0.985, $\alpha$=0.98, $\beta$=0.19) | 10.23 | 0.59 |

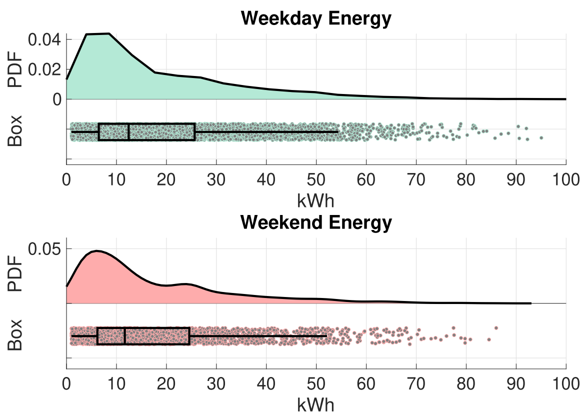


**FIGURE 13.** Energy transfer analysis for 7 kW chargers.

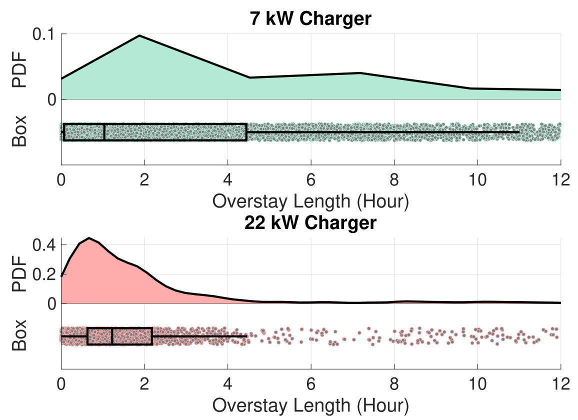


**FIGURE 15.** Overstay (hr) analysis for 7 kW and 22 kW chargers.

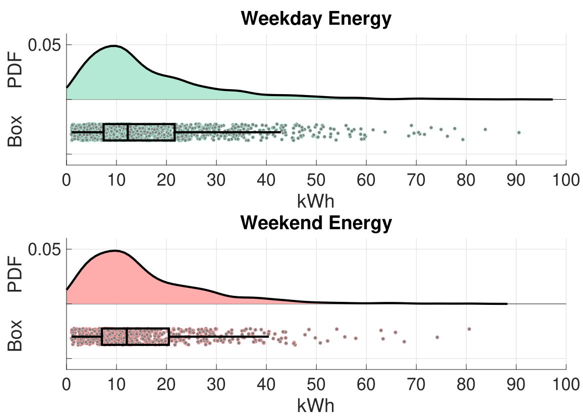


**FIGURE 14.** Energy transfer analysis for 22 kW chargers.

an energy demand that is adequate for charging only a portion of the battery, rather than reaching a full 100% state of charge. This is also because our dataset does not include domestic or workplace charging. Hence, energy transfer is limited by the parking duration.

In Figure 14, energy transfer analysis is presented for 22 kW chargers. It can be seen that for weekdays, first, second, and third quartiles are 7.42 kWh, 12.26 kWh, and 21.1 kWh, respectively. The results for weekend analysis is similar and first, second, and third quartiles are 7.08 kWh, 12.06 kWh, and 19.7 kWh, respectively. It can be seen that energy transfer characteristics is consistent for both charger types and weekday/weekend charging sessions. From Figure 14, the following observations can be made. The energy demand of 22 kW chargers show a similar usage pattern as 7 kW chargers. This is mainly because the charging rates are limited for some customers and EVs are charged with lower than 22 kW. Moreover, 22 kW chargers are primarily used to complement domestic charging. Therefore, parking fees and restrictions shape the charing demand. This can be observed from Figures 11 and 12 which show the sojourn durations. While 7 kW chargers allow for long sojourn durations (multi-storey car parks, etc.), 22 kW chargers are limited by the parking restrictions.

## V. OVERSTAY AND FLEXIBILITY ANALYSIS

As discussed in Section IV-B, almost all EV sessions include an overstay (percentage of time plugged in and not charging). Over the next decades, when EVs gain mainstream acceptance, overstay will be a major issue as other vehicles will not be able to use the chargers. However, under today's relatively low electrification rates, overstay periods promise opportunities for demand flexibility through smart charging. Therefore, this section presents the analysis of overstay and peak load reduction potential. The mathematical parameters used in this section are explained in Table 5.

**TABLE 5. Summary of mathematical parameters used in statistical analysis and optimization.**

| Parameter | Description |
|---|---|
| $PD$ | Parking duration hours |
| $CC$ | Unit charging cost (GBP/kWh) |
| $ST$ | Charging start time (hh:mm) |
| $i$ | EV index |
| $s$ | Time step (one-minute resolution) |
| $P_{is}$ | Peak charging rate for EV $i$ at time step $s$ in kW |
| $D_i$ | Total demand of EV $i$ in kWh |
| $r$ | Parameter to set minimum energy percentage |
| $C_{min}$ | Minimum charging rate of EVs in kW |
| $C_{max}$ | Maximum charging rate of EVs in kW |
| $C_s$ | Time of Use charging tariff in Table 6 |

## A. STATISTICAL ANALYSIS

The individual overstay periods for each session are calculated using Equation (4). In Figure 15, raincloud plots for overstay periods (7 kW and 22 kW chargers) are presented. It can be seen that the overstay lengths for 7 kW chargers are significantly higher than those for 22 kW chargers and exhibit higher variability. The first three quartiles for the 7 kW charger are 0.16, 1.03, and 4.35 hours, respectively. This shows that more than half of the charging events have an overstay period that is longer than 1.03 hours, while 25% of the charging events have an overstay that is longer than 4.35 hours.

In the 22 kW charging case, the overstay lengths are comparable to the 7 kW case, as the first quartile and the median values are 0.7 and 1.2, respectively. On the other hand, the third quartile is nearly half of the 7 kW case and is 2.2 hours. This is in parallel with the findings made in Section IV-D, as overnight chargings are limited in the 22 kW case. Moreover, as explained earlier, the number of 22 kW chargers is significantly less than 7 kW ones, and most 22 kW chargers are located in areas with parking restrictions during the day. Therefore, overstay periods (shown in Figure 15) beyond the third quartile are significantly lower than in the 7 kW charger case. The results show that overstay periods present a significant opportunity for smart charging. On the other hand, it is further critical to understand the factors affecting overstay periods. Hence, a metamodel is presented in the next section to analyze this.

## B. METAMODELING OF OVERSTAY

The previous section shows that there is high variability in overstay lengths due to various reasons, such as the cost of EV charging, parking duration, and start of the charging session. To estimate the weight of each factor, a metamodel is developed. Using the Response Surface Methodology (RSM), an approximate second-order polynomial model for the functional relationship between overstay length $f_O$ and other critical parameters, namely parking duration $PD$, unit cost of EV charging $CC$, and the start time of the charging session $ST$, is calculated. The RSM gives a parametric functional relationship between $f_O$ and the other parameters ($f_O = f(PD, CC, ST)$) [47], [48]. In the dataset, the sojourn times (parking durations) are given in the previous sections and take values between 0.1 and 31 hours. The cost of charging (per kWh) takes values between 0 and 0.65 GBP, and the start time takes values between 0 and 24 hours. The resultant RSM equation is given below is calculated using Matlab for overstay lengths less than 24 hours,

$$\begin{aligned} f_O = &-0.707 + 0.509 \times PD - 0.023 \times CC + 0.134 \times ST \\ &-0.383 \times PD \times CC - 0.001 \times PD \times ST + 0.053 \times CC \times ST \\ &+ 0.018 \times PD^2 - 0.605 \times CC^2 - 0.004 \times ST^2 \end{aligned} \tag{6}$$

For the above regression model, the R-Square statistic is 87%, and the mean square root error is 1.49%. These statistic imply that the input parameters for the given ranges provide a meaningful relationship to explain how overstay periods are shaped by each input parameters. If the polynomial value has a positive sign, it means there is a positive correlation between the overstay length ($f_O$) and that parameter (e.g., *PD*). To understand the weight (or sensitivity) of each parameter, the second-order derivatives of the quadratic parameters are calculated:

$$\frac{\partial^2 f_O}{\partial PD^2} = 0.018, \tag{7}$$

$$\frac{\partial^2 f_O}{\partial CC^2} = -0.605, \tag{8}$$

$$\frac{\partial^2 f_O}{\partial ST^2} = -0.004. \tag{9}$$

From the above differentiations, the following conclusions can be drawn. The overstay lengths ($f_O$) increase as the overall parking duration (PD) increases (from equation (7)). Charging cost (CC) has the highest weight on overstay lengths (from equation (8)), and overstay durations ($f_O$) decrease as the cost of charging (CC) increases (from equation (9)). Finally, there is a weak relationship between overstay lengths and the time to start charging. This means late-night chargings are kept slightly shorter, as most charging locations do not allow overnight charging.

## C. SMART CHARGING POTENTIAL

The overstay analysis given above indicates that EVs' overstay periods can be used for smart charging to reduce the peak charging rate for a given region. Smart charging is the exploitation of the flexibility within the charging process that could be used to reduce peaks and to achieve other optimization objectives, such as avoiding grid congestions, lowering price spikes, or cultivating excess renewable energy. Smart charging can be achieved primarily in two ways: (i) central and (ii) distributed way. In the first method, a central entity keeps track of all EV charging events and sends signals to each charger via two-way communication systems. In the second method, there is no communication between different EVs, and each EV solves its own optimization problem to achieve an objective, such as minimizing the average peak rate or charging cost. In this section, a case study is provided with distributed control where each EV $i$ aims to minimize the sum of the ratio of the peak charging rate $P_{is}$ for each time step $s$ to the requested demand $D_i$ in the sojourn period $S_i$, i.e.,

$$\text{Minimize } -\sum_s \frac{1}{s}\frac{P_{is}}{D_i}. \tag{10}$$

Note that the minimum objective can be achieved when the total transferred energy is equal to the energy demand. The optimization problem is subject to the following constraints:

$$rD_i \leq \sum_s P_{is} \times \frac{s}{60} \leq D_i, \ \forall i \tag{11}$$

$$P_{is} \in \{0\} \cup [C_{min}, C_{max}], \ \forall s, \forall i \tag{12}$$

$$s \in S_i, \ \forall i. \tag{13}$$

Equation (11) is the energy constraint, which shows that the sum of energy transfer should be at least $rD_i$, where $r$ a parameter between 0 and 1 and is set to 0.95. This constraint also shows that the energy transfer is upper limited by the requested energy demand $D_i$. The second constraint (12) shows that charge rate can take values between minimum charging rate $C_{min}$ which is usually 1.1 kW, and $C_{max}$ which the maximum charger rate, that is 7 kW or 22 kW. Note that most chargers cannot assign charger rate between 0 and 1.1 kW as this band reserved for communication purposes [49]. The first constraint (11) relaxes the energy constraint to account for infeasible charging rates that are lower than 1.1 kW. The time step is set as one minute, therefore, to calculate the energy transferred in one minute, the charging power is multiplied by $\frac{1}{60}$ in (11). Moreover, given the linear nature of the constraints and the objective function, the smart charging is solved using the Interior Point Algorithm in Matlab. In Figure 16, distributed control results are compared with uncontrolled charging case for an average daily load for one week. The average load reduction across the week is 30.25%. In 85% of the time the peak load has been reduced, and 15% the load was equal to higher than the uncontrolled case due to "bouncing effect" which occurs when a load is shifted towards another peak period. Nevertheless, the proposed method shows that without the need for any communication systems, the system load could be reduced significantly. It is worthy noting that distributed optimisation further shaves the afternoon peak (e.g. 5 pm) that coincides with UK's peak electricity load. Average peak reduction for the evening peaks are presented in the bar graph of Figure 16. It can be seen that evening peaks can be reduced by 10% to 30%. Therefore, the real-world implementation could be beneficial for power grid operators to reduce overall electricity consumption.

Ref. [13] introduces a centralized smart charging algorithm that employs a quadratic objective function to minimize the total energy consumed during a specific time slot $s$. Similar to our model, electric vehicles (EVs) in their study are charged during their respective sojourn durations, allowing for flexibility in vehicle charging. However, there are two key distinctions between their model and ours. Firstly, our model is distributed, meaning that the charge schedule for a particular vehicle is unknown to other vehicles. Therefore, it is easier to implement. Secondly, our model incorporates the minimum charge rate ($C_{min}$) as a constraint. This constraint is of utmost importance from a technological standpoint since, in reality, vehicles cannot charge at rates below $C_{min}$ (i.e., between 0 and $C_{min}$).

**TABLE 6.** Commercial customer summer (June-September) energy and demand tariffs (USD per kW) adopted from pacific gas and electric [50].

| | Time Period | Energy Rate (USD/kWh) |
|---|---|---|
| Peak | 4 pm - 9 pm | 0.165 |
| Partial-Peak | 2 pm - 4 pm<br>9 pm - 11 pm | 0.135 |
| Off-Peak | All other hours | 0.114 |

### D. LOAD SHIFTING WITH TIME OF USE TARIFFS

The flexibility of EV charging sessions could also be exploited using Time-of-Use (ToU) based electricity tariffs for EV charging. In ToU, tariffs, unit electricity price varies over time and typically higher during peak hours to discourage EV charging to lower the peak electricity demand. In this case study, EV charging tariffs from Pacific Gas and Electric, a utility company in San Diego, California, are used and details are given in Table 6.

In this case, the objective function of the optimisation function becomes

$$\text{Minimize } -\sum_s C_s \frac{1}{s}\frac{P_{is}}{D_i}, \tag{14}$$

where $C_s$ is the energy rate as given in Table 6.

In this case study, the EV charging events in London during weekdays are considered. Moreover, the focus is on lowering evening peaks occurring from EV charging. Therefore, charging sessions after 4 pm are chosen and smart charging framework given in objective function (14) and constraints (11), (12), and (13) is solved. As shown in Figure 17, the evening peak at 8 pm is shifted to after midnight (at 4 am) without requiring EV owners to stay extra longer. The primary reason for this shift is the lower offpeak tariffs. In this case study, a total of 240 EVs with different attributes (start time, departure time, demand). The total cost of charging under no control scenario is 8681.5 USD, while optimised charging reduces this cost to 7144.9 USD (17.7% cost reduction). Similar to the previous scenario, if the chargers have information about all other EVs and their schedules, then a more flat load profile could be achieved. However, real-time access to such information in physically distant charging networks is often constrained by company policies and other data protection policies. Hence, our case studies are limited to distributed charging cases as presented in this and the previous sections.

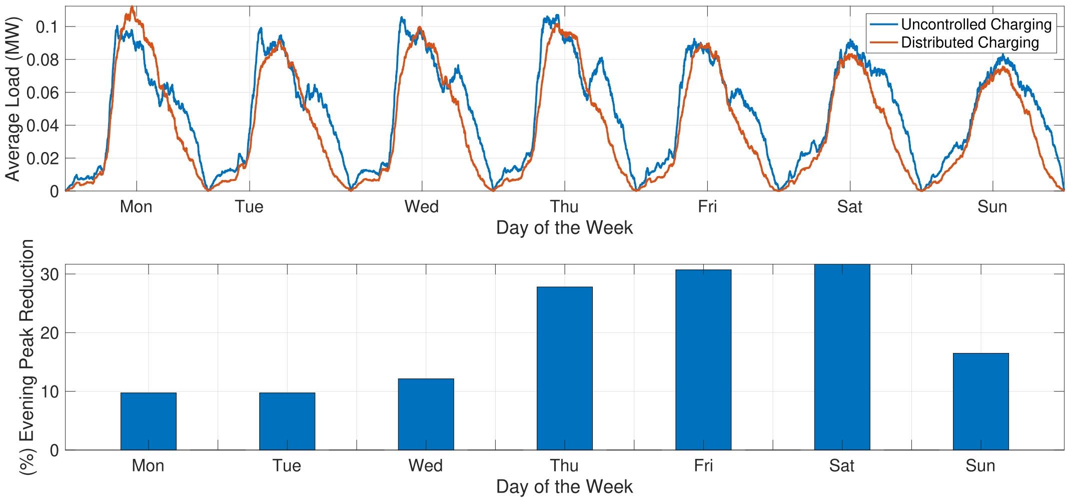


**FIGURE 16.** Comparison of distributed and uncontrolled charging cases. Average load reduction over the week is 30.25%. % of evening demand is calculated for average load between 4:30 pm - 5:30 pm.

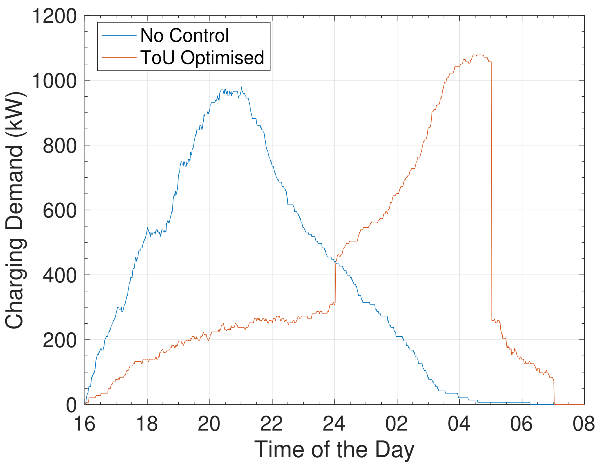


**FIGURE 17.** Smart charging to shift the peak load to off-peak periods using time of use prices.

## VI. CONCLUSION

### A. SUMMARY OF FINDINGS

In this paper, statistical characterization of the first public AC charging sessions across the UK for four months (April – July 2022) has been presented. The dataset includes 7 kW and 22 kW chargers with nearly twelve thousand sessions. Firstly, utilisation rates for each charger type were analyzed. It was shown that the utilisation rates are slightly lower than those in Nordic countries such as Sweden and Finland, but higher than the US case. Secondly, the machine learning DBSCAN algorithm was used to cluster the charging sessions based on arrival and departure times and showed that 82% of the charging sessions occur during the daytime. As a consequence, the dataset is classified as weekend/weekdays and by charger type. Using raincloud analysis, empirical probability distribution functions and descriptive statistics were analyzed and presented for arrival, departure, sojourn, overstay, and energy transfer sessions. The inter-arrival times were fitted to well-known probability distribution functions, and a goodness-of-fit test was carried out using the Chi-square test. It was shown that exponential inter-arrival times, dominantly in queuing-based modeling, are reasonable. An RSM-based metamodel to quantify the factors affecting overstay lengths was developed. It was shown that the cost of EV charging is the most important parameter determining overstay durations. Finally, we presented two case studies that demonstrate the utilisation of overstay periods by employing reduced charging rates, resulting in a reduction of the overall electric vehicle (EV) charging load. The first case study focuses on scheduling techniques that aim to minimize peak usage. In the second case study, we explored the effectiveness of time-of-use prices in targeting specific time periods, such as peak electricity usage hours, to further decrease the EV load. The results showed that, even with the distributed case, smart charging could lead to an average of 30% savings. The load curves further show that the peak durations of public chargers occur 2-3 hours earlier than domestic EV charging, which peaks around 7-8 pm [51].

### B. LIMITATIONS OF THE STUDY

The limitations of this study can be listed as follows. Firstly, our dataset covers four months (April-July), hence there could be differences in energy demand in other seasons such as winter due to cold weather and shorter daylight hours. For instance, in August and February, the percentage of annual trips per month drops compared to other months [46]. Secondly, our dataset includes transferred energy and does not include instantaneous charging power. Therefore, it is assumed that the charging power is constant throughout the charging session. In reality, the actual charging power will be slightly lower than the peak rate due to efficiency losses, weather, and limitations of specific EVs, particularly for 22 kW chargers. For instance, Tesla Model 3 has a maximum

AC charging rate of 11 kW, while Renault Zoe can accept a 22 kW AC charging rate. Therefore, even though sojourn durations would be the same, actual overstay periods are expected to be slightly shorter.

### C. OPEN RESEARCH QUESTIONS

The analysis presented in this study leads to the following future research directions. Firstly, as can be observed from Figure 3, there is significant variability in utilisation rates. Further investigation is needed to understand the factors (e.g., driving pattern, access to domestic charging, EV adoption rates) affecting the utilisation rates, which can strongly influence future charger deployment projects

## REFERENCES

[1] T. D. Guzel and K. Alp, ''Modeling of greenhouse gas emissions from the transportation sector in Istanbul by 2050,'' *Atmos. Pollut. Res.*, vol. 11, no. 12, pp. 2190–2201, Dec. 2020.

[2] G. Bruckmann, F. Willibald, and V. Blanco, ''Battery electric vehicle adoption in regions without strong policies,'' *Transp. Res. D, Transp. Environ.*, vol. 90, Jan. 2021, Art. no. 102615.

[3] M. Muratori, E. Kontou, and J. Eichman, ''Electricity rates for electric vehicle direct current fast charging in the United States,'' *Renew. Sustain. Energy Rev.*, vol. 113, Oct. 2019, Art. no. 109235.

[4] B. Borlaug, F. Yang, E. Pritchard, E. Wood, and J. Gonder, ''Public electric vehicle charging station utilization in the United States,'' *Transp. Res. D, Transp. Environ.*, vol. 114, Jan. 2023, Art. no. 103564.

[5] *Electric Vehicle and Alternatively Fuelled Vehicle Registrations*. Accessed: Feb. 2023. [Online]. Available: https://www.smmt.co.uk/vehicle-data/evs-and-afvs-registrations/

[6] *Electric Vehicles—Worldwide*. Accessed: Feb. 2023. [Online]. Available: www.statista.com/outlook/mmo/electric-vehicles/worldwide

[7] M. Wicki, G. Bruckmann, and T. Bernauer, ''How to accelerate the uptake of electric cars? Insights from a choice experiment,'' *J. Cleaner Prod.*, vol. 355, Jun. 2022, Art. no. 131774.

[8] G. Bruckmann and T. Bernauer, ''An experimental analysis of consumer preferences towards public charging infrastructure,'' *Transp. Res. D, Transp. Environ.*, vol. 116, Mar. 2023, Art. no. 103626.

[9] I. S. Bayram, U. Zafar, and S. Bayhan, ''Could petrol stations play a key role in transportation electrification? A GIS-based coverage maximization of fast EV chargers in urban environment,'' *IEEE Access*, vol. 10, pp. 17318–17329, 2022.

[10] S. Hardman and G. Tal, ''Understanding discontinuance among California's electric vehicle owners,'' *Nature Energy*, vol. 6, no. 5, pp. 538–545, Apr. 2021.

[11] M. Smith and J. Castellano, ''Costs associated with non-residential electric vehicle supply equipment: Factors to consider in the implementation of electric vehicle charging stations,'' U.S. Dept. Energy, Washington, DC, USA, Tech. Rep. DOE/EE-1289, 2015.

[12] M. Gellrich, A. Block, and N. Leikert-Böhm, ''Spatial and temporal patterns of electric vehicle charging station utilization: A nationwide case study of Switzerland,'' *Environ. Res., Infrastruct. Sustainability*, vol. 2, no. 2, Jun. 2022, Art. no. 021003.

[13] N. Sadeghianpourhamami, N. Refa, M. Strobbe, and C. Develder, ''Quantitive analysis of electric vehicle flexibility: A data-driven approach,'' *Int. J. Electr. Power Energy Syst.*, vol. 95, pp. 451–462, Feb. 2018.

[14] C. Develder, N. Sadeghianpourhamami, M. Strobbe, and N. Refa, ''Quantifying flexibility in EV charging as DR potential: Analysis of two real-world data sets,'' in *Proc. IEEE Int. Conf. Smart Grid Commun. (SmartGridComm)*, Nov. 2016, pp. 600–605.

[15] T. Zeng, H. Zhang, and S. Moura, ''Solving overstay and stochasticity in PEV charging station planning with real data,'' *IEEE Trans. Ind. Informat.*, vol. 16, no. 5, pp. 3504–3514, 2020.

[16] T. Zeng, S. Bae, B. Travacca, and S. Moura, ''Inducing human behavior to maximize operation performance at PEV charging station,'' *IEEE Trans. Smart Grid*, vol. 12, no. 4, pp. 3353–3363, Jul. 2021.

[17] *Tesla Idle Fees*. Accessed: Mar. 2023. [Online]. Available: https://www.tesla.com/support/supercharger-idle-fee

[18] T. Jonas, N. Daniels, and G. Macht, ''Electric vehicle user behavior: An analysis of charging station utilization in Canada,'' *Energies*, vol. 16, no. 4, p. 1592, Feb. 2023.

[19] K. L. Lim, S. Speidel, and T. Bräunl, ''A comparative study of AC and DC public electric vehicle charging station usage in Western Australia,'' *Renew. Sustain. Energy Transition*, vol. 2, Aug. 2022, Art. no. 100021.

[20] M. Neaimeh, S. D. Salisbury, G. A. Hill, P. T. Blythe, D. R. Scoffield, and J. E. Francfort, ''Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles,'' *Energy Policy*, vol. 108, pp. 474–486, Sep. 2017.

[21] I. S. Bayram, V. Zamani, R. Hanna, and J. Kleissl, ''On the evaluation of plug-in electric vehicle data of a campus charging network,'' in *Proc. IEEE Int. Energy Conf. (ENERGYCON)*, Apr. 2016, pp. 1–6.

[22] Z. Jiang, H. Tian, M. J. Beshir, R. Sibagatullin, and A. Mazloomzadeh, ''Statistical analysis of electric vehicles charging, station usage and impact on the grid,'' in *Proc. IEEE Power Energy Soc. Innov. Smart Grid Technol. Conf. (ISGT)*, Sep. 2016, pp. 1–5.

[23] S. I. Spencer, Z. Fu, E. Apostolaki-Iosifidou, and T. E. Lipman, ''Evaluating smart charging strategies using real-world data from optimized plugin electric vehicles,'' *Transp. Res. D, Transp. Environ.*, vol. 100, Nov. 2021, Art. no. 103023.

[24] M. Baresch and S. Moser, ''Allocation of e-car charging: Assessing the utilization of charging infrastructures by location,'' *Transp. Res. A, Policy Pract.*, vol. 124, pp. 388–395, Jun. 2019.

[25] K. M. Tan, V. K. Ramachandaramurthy, and J. Y. Yong, ''Integration of electric vehicles in smart grid: A review on vehicle to grid technologies and optimization techniques,'' *Renew. Sustain. Energy Rev.*, vol. 53, pp. 720–732, Jan. 2016.

[26] M. Nour, J. P. Chaves-Ávila, G. Magdy, and Á. Sánchez-Miralles, ''Review of positive and negative impacts of electric vehicles charging on electric power systems,'' *Energies*, vol. 13, no. 18, p. 4675, Sep. 2020.

[27] S. Rahman, I. A. Khan, A. A. Khan, A. Mallik, and M. F. Nadeem, ''Comprehensive review & impact analysis of integrating projected electric vehicle charging load to the existing low voltage distribution system,'' *Renew. Sustain. Energy Rev.*, vol. 153, Jan. 2022, Art. no. 111756.

[28] I. Sharma, C. Cañizares, and K. Bhattacharya, ''Smart charging of PEVs penetrating into residential distribution systems,'' *IEEE Trans. Smart Grid*, vol. 5, no. 3, pp. 1196–1209, May 2014.

[29] J. de Hoog, T. Alpcan, M. Brazil, D. A. Thomas, and I. Mareels, ''Optimal charging of electric vehicles taking distribution network constraints into account,'' *IEEE Trans. Power Syst.*, vol. 30, no. 1, pp. 365–375, Jan. 2015.

[30] P. Richardson, D. Flynn, and A. Keane, ''Optimal charging of electric vehicles in low-voltage distribution systems,'' *IEEE Trans. Power Syst.*, vol. 27, no. 1, pp. 268–279, Feb. 2012.

[31] M. Muratori, ''Impact of uncoordinated plug-in electric vehicle charging on residential power demand,'' *Nature Energy*, vol. 3, no. 3, pp. 193–201, Jan. 2018.

[32] A. Ahmadi, A. Tavakoli, P. Jamborsalamati, N. Rezaei, M. R. Miveh, F. H. Gandoman, A. Heidari, and A. E. Nezhad, ''Power quality improvement in smart grids using electric vehicles: A review,'' *IET Electr. Syst. Transp.*, vol. 9, no. 2, pp. 53–64, Jun. 2019.

[33] K. Chaudhari, N. K. Kandasamy, A. Krishnan, A. Ukil, and H. B. Gooi, ''Agent-based aggregated behavior modeling for electric vehicle charging load,'' *IEEE Trans. Ind. Informat.*, vol. 15, no. 2, pp. 856–868, Feb. 2019.

[34] J. Su, T. T. Lie, and R. Zamora, ''Modelling of large-scale electric vehicles charging demand: A new Zealand case study,'' *Electric Power Syst. Res.*, vol. 167, pp. 171–182, Feb. 2019.

[35] F. Schulz and J. Rode, ''Public charging infrastructure and electric vehicles in Norway,'' *Energy Policy*, vol. 160, Jan. 2022, Art. no. 112660.

[36] S. Á. Funke, F. Sprei, T. Gnann, and P. Plötz, ''How much charging infrastructure do electric vehicles need? A review of the evidence and international comparison,'' *Transp. Res. D, Transp. Environ.*, vol. 77, pp. 224–242, Dec. 2019.

[37] *UK Met Office*. Accessed: May 2023. [Online]. Available: https://www.metoffice.gov.uk/

[38] *Here is How EV Drivers Charge Their Cars Across Europe*. Accessed: Mar. 2023. [Online]. Available: https://www.virta.global/blog/how-are-we-charging-a-deep-dive-into-the-ev-charging-station-utilization-rates

[39] *Electric User Habits of Electric Vehicles in Finland*, The Finnish Information Centre of Automobile Sector, Helsinki, Finland, 2020.

[40] *EV Smart Chargepoint Survey 2022*, Dept. Bus., Energy Ind. Strategy, London, U.K., 2023.

[41] D. Xu and Y. Tian, "A comprehensive survey of clustering algorithms," *Ann. Data Sci.*, vol. 2, no. 2, pp. 165–193, Jun. 2015.

[42] M. Allen, D. Poggiali, K. Whitaker, T. R. Marshall, and R. A. Kievit, "Raincloud plots: A multi-platform tool for robust data visualization," *Wellcome Open Res.*, vol. 4, p. 63, Apr. 2019.

[43] I. S. Bayram, M. Devetsikiotis, and R. Jovanovic, "Optimal design of electric vehicle charging stations for commercial premises," *Int. J. Energy Res.*, vol. 46, no. 8, pp. 10040–10051, Jun. 2022.

[44] S. Esmailirad, A. Ghiasian, and A. Rabiee, "An extended M/M/K/K queueing model to analyze the profit of a multiservice electric vehicle charging station," *IEEE Trans. Veh. Technol.*, vol. 70, no. 4, pp. 3007–3016, Apr. 2021.

[45] J. L. Devore, *Probability and Statistics for Engineering and the Sciences*. Boston, MA, USA: Cengage Learning, 2015.

[46] I. Koncar and I. S. Bayram, "A probabilistic methodology to quantify the impacts of cold weather on electric vehicle demand: A case study in the UK," *IEEE Access*, vol. 9, pp. 88205–88216, 2021.

[47] R. H. Myers, D. C. Montgomery, and C. M. Anderson-Cook, *Response Surface Methodology: Process and Product Optimization Using Designed Experiments* (Wiley Series in Probability and Statistics), 3rd ed. Hoboken, NJ, USA: Wiley, Jan. 2009.

[48] I. S. Bayram, G. Michailidis, M. Devetsikiotis, and F. Granelli, "Electric power allocation in a network of fast charging stations," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 7, pp. 1235–1246, Jul. 2013.

[49] K. Sevdari, S. Striani, P. B. Andersen, and M. Marinelli, "Power modulation and phase switching testing of smart charger and electric vehicle pairs," in *Proc. 57th Int. Universities Power Eng. Conf. (UPEC)*, Aug. 2022, pp. 1–6.

[50] I. S. Bayram, S. Galloway, and G. Burt, "A probabilistic capacity planning methodology for plug-in electric vehicle charging lots with on-site energy storage systems," *J. Energy Storage*, vol. 32, Dec. 2020, Art. no. 101730.

[51] eEnergy, *Electric Vehicle Charging Behaviour Study*, 2Element Energy, Cambridge, U.K., 019.

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