CHARACTERISTIC DEMAND PROFILES OF RESIDENTIAL AND COMMERCIAL EV USERS AND OPPORTUNITIES FOR SMART CHARGING

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ABSTRACT

This paper characterises electric vehicle (EV) charging demand for different user types based on the data collected within the Low Carbon London (LCL) EV trial. The trial collected charging and driving data for residential and commercial vehicle fleets, as well as for public charging stations in London. The paper uses EV trial data to identify characteristic charging patterns that can be used by Distribution Network Operators for network planning purposes, including the evaluation of diversity of aggregate EV demand. The paper further investigates the opportunities for smart management of residential EV charging demand based on actual journey data and uses a peak demand management model to optimise charging decisions while respecting the vehicle usage constraints. A set of recommendations is finally provided to support EV integration into network planning.

INTRODUCTION

Electrification of road transport is becoming a prominent element of decarbonisation policy in the energy sector, accompanied with a high share of low-carbon electricity supplied by renewable and other low-carbon generation technologies. A transport sector based on EVs could be characterised by significant flexibility in terms of when the vehicles charge, creating opportunities for utilising more efficient charging strategies from the system perspective. Transport sector based on EVs would be characterised by significant flexibility in terms of the timing of energy delivery, and this opens up opportunities for utilising more efficient charging strategies, not only to optimise electricity generation, but also to enhance the efficient usage of network capacity [1],[2]. System characterised by a high penetration of intermittent renewable resources may benefit significantly from using EV charging load as flexible demand that can be shifted towards periods of surplus energy [3]. Benefits of smart EV charging for a more efficient integration of wind generation in the future UK system are explored in detail in [4].

Despite the prominence of EVs in the decarbonisation policy, there is still limited body of evidence on actual EV usage and charging patterns to allow a comprehensive impact assessment of EV demand on the electricity system. Most of the previous assessments in this respect (e.g. [5] or [6]) have thus relied on usage data for conventional vehicles to infer possible EV charging behaviour. It is therefore vitally important to study the realistic behaviour of EV users in order to evaluate the potential impact of EV demand on the system and identify opportunities for deploying more efficient charging strategies.

In that context, this paper presents the key findings arising from the Low Carbon London (LCL) electric vehicle (EV) trial. The trial involved both residential and commercial vehicle fleets, as well as charging data collected from Source London public charging stations. The key objective of the paper is to use the extensive volume of collected EV trial data to comprehensively characterise EV charging demand. This will include identifying typical charging patterns for both average and worst-case scenarios, which can be used by Distribution Network Operators (DNOs) to estimate the additional electricity demand for EV charging and support network planning. In this paper we also assess the opportunities for smart charging of EVs with the objective to provide grid support while respecting the constraints related to the EV users' journey patterns.

TRIAL DESCRIPTION

The EV data collected in the LCL trial covered three broad areas:

- Metered EV charging data from dedicated charging stations in 10-minute resolution for residential and commercial EV fleets
- Data on charging events collected at Source London public charging stations
- Vehicle logger data recording driving, charging and parking events

Charging data

Data from remote meters installed at dedicated charging stations recorded active and reactive power as well as other electrical parameters in 10-minute resolution. The number of vehicles involved as well as the volume of metered data is shown in Table 1.

Table 1. Parameters of charging data collected for residential and commercial EV fleets

	Sample	
	Residential	**Commercial**
Total number of meters	72	54
Meters with validated active power measurements	54	26
Total number of active power measurements	2.35m	0.95m
Equivalent days per EV	302	255
Start date	2 Apr 2013	19 Feb 2013

Participants in the commercial EV trial fell into several distinct categories: 1) electric delivery vans (connected to 3-phase meters; all other commercial EVs were connected to 1-phase meters); 2) a car pool owned by Transport for London; and 3) company cars. Given the very specific charging patterns and energy requirements of delivery vans, their analysis will be presented separately from the rest of the commercial participants.

Public charging points

The EV trial also collected data associated with public charging points (CPs) in London run by four different Charging Network Operators (CNOs). The data included charging events recorded at 491 different stations, of which 391 CPs had satisfactory data quality. Unlike in the residential and commercial trials, charging events were logged when they happened rather than having continuous measurements.

Vehicle logger data

As part of the EV trial, a subset of EVs has been equipped with detailed journey data loggers that recorded three types of events: Driving (D), Parking (P) and Charging (C). A number of quantitative parameters were associated with each of the events such as: vehicle ID, start/end times and locations, distance travelled, average and maximum speed, start/end battery State of Charge (SoC), energy transferred etc.

The logger data covered 22 residential and 8 commercial vehicles with the data spanning about one year. Ten of the residential EV users with data loggers were also equipped with remote charging data metering i.e. participated in the residential EV charging trial. Due to various technical issues (e.g. interference between loggers and batteries) the logger data coverage was not complete, i.e. a significant number of D/P/C events went unrecorded. The logger data are therefore used only to make relative comparisons rather than make conclusions about the energy requirements or mileage driven.

CHARGING DATA ANALYSIS

Residential users

Most residential EVs charged at 3.7 kW (i.e. 16 A), although both higher (up to 7.4 kW) and lower (1.7 kW) values of maximum charging power were also observed. Most of the charging events lasted for a few hours.

Charging profiles

Average charging profiles for the residential EV sample are found by computing the average values observed in each of the 144 10-minute intervals during the day (Figure 1). Average charging power values are found across all EVs and across all days of a given type (for instance, the Sunday profile is averaged across all EVs and all Sundays).

Peak demand for residential EV charging demand occurred around 9pm in the evening, with the bulk of charging energy supplied between 6pm and midnight. Average daily charging demand was 3.52 kWh, with higher values observed on workdays (3.68 kWh) than during weekends (3.09 kWh). Assuming a specific consumption of 0.2 kWh/km, this would correspond to an average daily distance of 17.5 km, which is below the national average for conventional cars of around 30 km. Maximum value of average demand per EV is around 0.3 kW for an average day, increasing to 0.33 kW for an average workday, while the highest maximum value of 0.38 kW was observed on Thursdays.

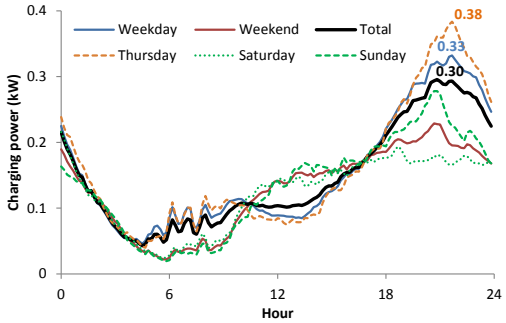

Figure 1. Average charging profiles per EV for different days of week

Residential EVs spent on average 7.8% of time charging (just below 2 hours per day). From the 9,909 charging events, more than 95% took less than 5 hours, and shorter events tended to be more frequent.

In the network planning process it is necessary to know the maximum aggregate EV demand that can be reasonably expected. The maximum value of charging demand per EV was therefore found across the trial period for each 10-minute interval during the day (this can be considered as a "worst-case" scenario for the analysed EV sample). The resulting profile ("Maximum") is compared to the average profile as shown in Figure 2.

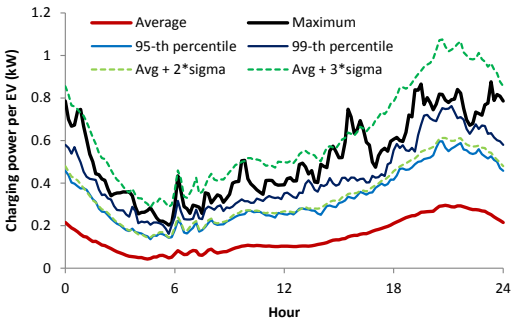

Figure 2. Maximum expected charging profiles per EV for different probability levels

The maximum demand per EV was 0.88 kW, or about 3 times higher than the highest average demand. This value can be interpreted as the *diversified peak demand* for the residential EV sample. The *non-diversified* maximum demand per EV was around 3.5 kW, implying the *coincidence factor* of around 25%. Figure 2 also quantifies the 95th and 99th percentiles of observations in each interval, as well as average plus 2 or 3 standard deviations.

EV demand diversity

In the context of an increasing EV uptake, it is important to estimate the functional relationship between their diversified peak and the size of EV population. For that purpose, the maximum demand profiles have been quantified for the sample size of 10, 21, 32, 43 and 54 vehicles, where all subsamples below 54 vehicles were drawn

randomly 10 times from the full sample. The relationship between the coincidence factor (CF) and the sample size is depicted in Figure 3 (the theoretical 100% value is also included for reference), as well as the maximum and minimum values across all 10 random draws.

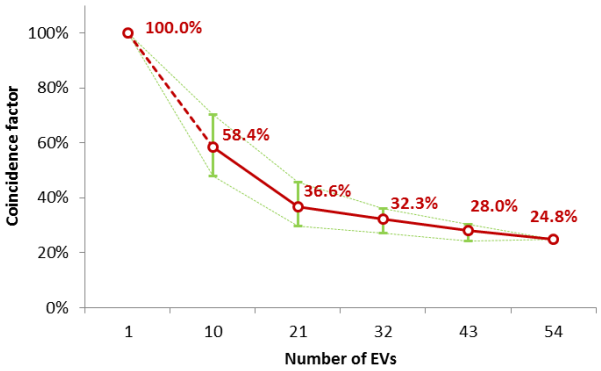

Figure 3. Coincidence factor for different subsample sizes of residential EVs

The results suggest a very regular relationship between the CF and sample size, with a steady decline towards higher sample sizes. CF in this case seems to asymptotically approach 20% for very large samples. This parameter represents a critical input into network planning, driving the requirements for network infrastructure capacity.

Commercial users

Relatively smaller size and heterogeneity of the commercial EV sample make it more difficult to assess the diversity of commercial EV demand. 16 of the 26 commercial charging points had a 1-phase connection, mostly charging at 3.7 kW. The remaining 10 vehicles were delivery vans that had 3-phase connections and higher charging power of up to 14 kW. Average charging profiles for the two groups are shown in Figure 4 and Figure 5.

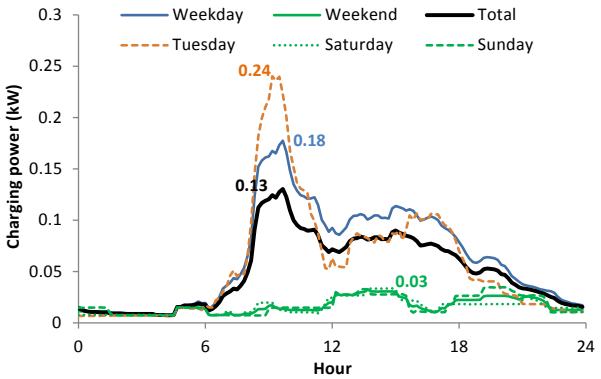

Figure 4. Average charging profiles per user among the single-phase commercial participants for different days of week

Peak demand for single-phase commercial participants occurred around 10am, while most of the charging energy was delivered between 8am and 8pm. This seems to suggest that many pool vehicles and company cars are plugged in around the start of business hours. Weekend charging demand was very low, as this is when most businesses and offices were closed. Variations among different workdays were also significant – e.g. the average peak on Tuesday was 0.24 kW, whereas on Friday it was only about 0.16 kW. Average daily energy was 1.45 kWh or about 2.5 times less than for residential EVs.

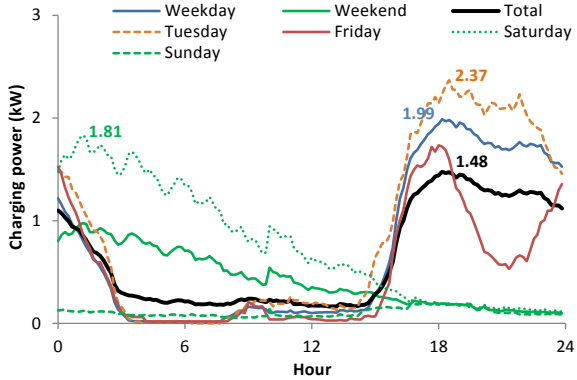

Figure 5. Average charging profiles per user among the 3-phase commercial participants for different days of week

Energy requirements and the peak demand of the 3-phase subgroup are an order of magnitude higher than in the first subgroup, due to the higher mileage driven by delivery vans and their higher consumption per kilometre. Their average daily charging consumption was 14.2 kWh. Typical charging patterns are also different: a rapid demand increase from virtually zero to about 2 kW occurs on weekday afternoons (4-5pm). Demand on Sundays is virtually zero, while on Saturdays it appears to tail off from charging started on Fridays. Coping with the rapid demand increase during workday afternoons may be challenging for the local network, given that the high power levels coincide with the current system peak.

Maximum instantaneous average demand (i.e. diversified peak) per EV for 1-phase commercial users was found to be 1.07 kW. When compared against the non-diversified peak demand per EV, this resulted in the coincidence factor for this subgroup of 29% (Figure 3 suggests that for the residential sample of the same size this would be around 50%). Delivery vans on the other hand had a much higher diversified peak of almost 6 kW per meter. Due to the synchronicity of plugging in the vans, the resulting coincidence factor was rather high at 86%.

Charging data suggest that single-phase commercial participants spent on average 2.3% of time charging (30 minutes per day), while delivery vehicles with 3-phase meters spent 17% (4 hours per day). Typical duration of individual charging events was also longer for the latter group, with 30% of events taking 6 hours or longer as opposed to virtually none for the 1-phase users.

Public charging stations

Cumulative distribution of energy per charging event for 16,309 recorded events is shown in Figure 6, disaggregated across the four CNOs, and also indicating the median values and 5th and 95th percentiles. Median energy for all CPs was 3.3 kWh, which varied between 3.1 and 5.2 kWh across different CNOs. Only a small proportion of charging events required the energy of over 20 kWh.

The intensity of usage of individual CPs over the trial period is expected to depend on factors such as installation date, location, and plug type and rating. Cumulative distributions of the number of charging events recorded per CP are given in Figure 7, disaggregated across differ-

ent CNOs. There are evidently great variations in usage intensity across different CPs, although in general the usage frequency is rather low – only 10% of CPs are used more than 100 times over the 16-month period.

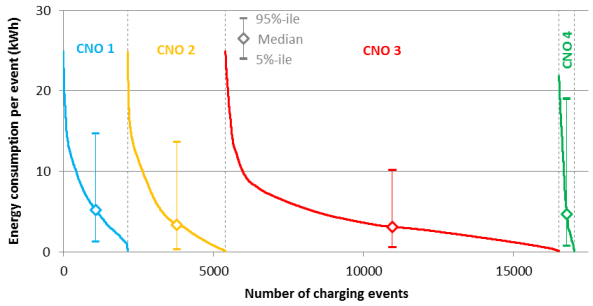

Figure 6. Cumulative distribution of energy per charging event for different CNOs

Using the unique vehicle ID information it was possible to establish that although some vehicles used public CPs very often (the maximum number of visits for a single EV was 675), most of them only used public CPs occasionally. The median number of visits was only 3 during the trial period, and the median consumption 12.8 kWh. A great majority of EV users (82%) used a public CP less than once a month, suggesting that early adopters appear to be using the public charging infrastructure more as an insurance policy at this stage. It was further observed that about 80% of vehicles visited up to 3 different public CPs over the trial period, while only 5% visited 7 or more.

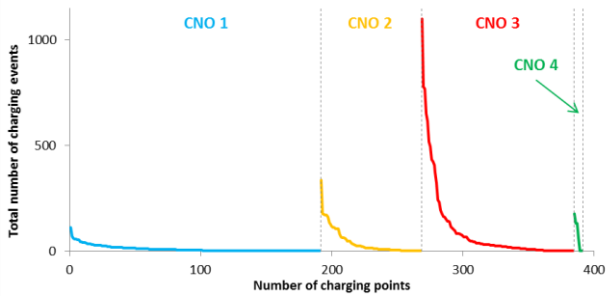

Figure 7. Cumulative distribution of total number of charging events per CP for different CNOs

Figure 8 plots pairs of values of energy and duration for each event; the correlation coefficient between the two variables is 0.53. Grouping of points can be clearly identified along the lines defined by the charging power levels of 2.35 kW (10 A) and 3.7 kW (16 A). Very few events are associated with the power of more than 3.7 kW, given that only a few CPs allowed fast charging.

If average and maximum charging profiles are constructed similar to residential and commercial demand, the average profile per CP peaks around noon at around 0.1 kW (with very little overnight usage), while the average daily energy is 1.18 kWh. The maximum instantaneous power per CP was about 1 kW. Energy consumption on working days (1.31 kWh) was higher than during the weekend (0.85 kWh).

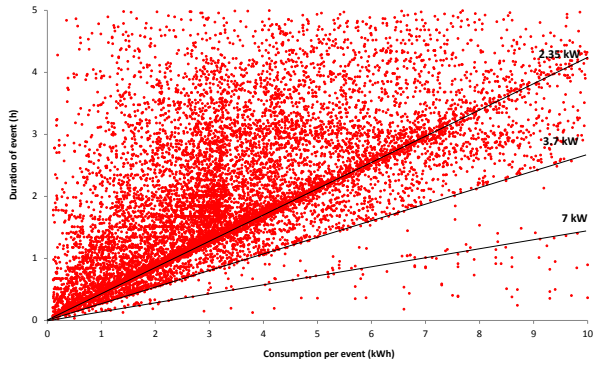

Figure 8. Scatter plot of charging energy vs. duration for individual events

JOURNEY DATA ANALYSIS

Data on driving, parking and charging patterns is valuable to establish the potential flexibility of EV charging demand. Due to the issues mentioned earlier, the charging energy captured by EV loggers is several times lower than the metered charging data, implying that the recorded distances also underestimate actual mileage. The specific consumption of electricity for the 22 residential vehicles was found to be 0.145 kWh/km; when accounting for charging losses in the order of 15%, the gross consumption was 0.17 kWh/km. Data on individual trips do not suggest significant differences in average (around 6.5 km) and median (3.5 km) distances per trip between residential and commercial participants. About 95% of trips were below 25 km for residential and below 20 km for commercial users.

SoC data showed that EV users plug in their vehicles at various levels of battery SoC. The scatter plot of start versus end SoC for residential users is presented in Figure 9. The most common end SoC values are between 90% and 98%, i.e. the batteries are mostly charged to the full (battery ageing and BMS may be preventing the ability to reach 100%).

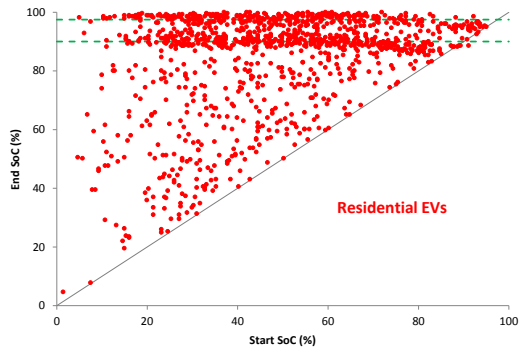

Figure 9. Scatter plot of start vs. end SoC for residential EVs

OPPORTUNITIES FOR SMART CHARGING

In this section the driving and charging data collected via data loggers are used to study the opportunities for smart EV charging to support network management i.e. minimise peak demand in the network, while respecting the constraints on the user side. An optimisation algorithm is developed for this purpose, and case studies are conduct-

ed with the fleets of 10 and 22 residential vehicles for a day in March 2014. The opportunity to manipulate EV demand is investigated while assuming EV demand is superimposed on a baseline residential demand profile.

The objective of the peak demand management model developed in this work was to optimise smart charging decisions in order to minimise the total peak demand in the local area (EV fleet plus local consumers). The model does this while respecting the when the EVs are parked and when on the road, allowing EV demand to be shifted only within the stationary periods immediately following charging events i.e. before the following journey begins. The model ensures that the same energy is delivered to the battery before the next journey is taken. The peak minimisation model was implemented as a linear programming model using the FICO Xpress platform [7].

The optimised charging profile for the case with 10 EVs is shown in Figure 10. Smart charging reduces the total peak to the level before introducing EVs. EV demand during peak hours is effectively reduced to zero, suggesting a high flexibility of EV demand.

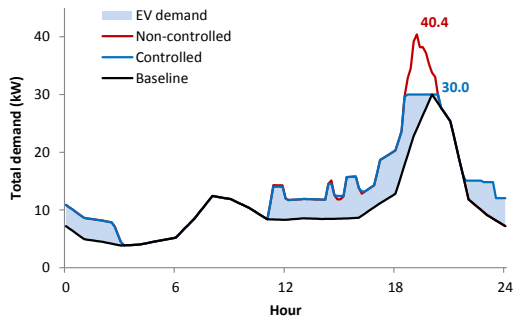

Figure 10. Uncontrolled and optimised charging profile for 10 residential EVs with baseline demand

The optimised charging schedule for the case of 22 EVs is presented in Figure 11. The peak demand for this case is reduced by 11.8 kW, however the EV demand in this case could not be reduced to zero during peak hours as one vehicle charged between 7pm and 8.30pm and made a journey immediately afterwards.

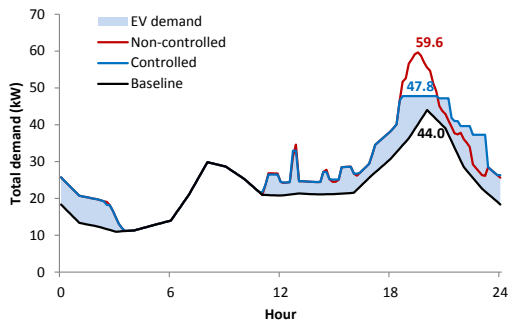

Figure 11. Uncontrolled and optimised charging profile for 22 residential EVs with baseline demand

The potential to shift residential EV charging demand without compromising the users' journey requirements seems significant. These results also validate the findings of a previous ENA report [5] that was based on charging behaviour inferred from conventional vehicles.

CONCLUSIONS AND RECOMMENDATIONS

The analysis has shown that the additional EV charging demand will depend on factors such as number of EVs, user type and day of the week. Understanding the expectations regarding the future uptake of EVs in a given distribution network therefore seems critical for appropriate planning of the network. The analysis also provides a basis for assessing the diversity of aggregate EV demand depending on the EV penetration.

Given the potential to use the flexibility of EV demand to support network management, as demonstrated in the case studies, the value of smart charging control should be thoroughly understood and taken into consideration in distribution network operation and planning. Evidence gathered in the LCL EV trials has demonstrated there are opportunities for adopting smart charging approaches to ensure a more efficient EV integration.

Expanding future trial activities to include more vehicles would provide further benefits in terms of boosting confidence in the results of the analysis. Moreover, understanding the specific behaviour of EV fleets might be of value, especially for market segments such as taxi fleets, public transport, other types of delivery fleets and company fleets, where the high usage i.e. high annual mileage is likely to make EVs even more attractive.

ACKNOWLEDGMENTS

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