Impact & opportunities for wide-scale EV deployment

Low Carbon London Learning Lab
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Executive Summary

This report describes the Low Carbon London trials involving Electric Vehicles (EV), providing the description of the EV fleets and the network of public and private charging points covered by the trial. A detailed analysis of the data collected during the EV trial is conducted, in order to characterise the new EV demand by identifying the key requirements associated with EV charging including energy per vehicle, charging power, temporal charging patterns and diversity of EV demand. Key features of EV charging profiles are characterised for residential, commercial or public charging points. To our knowledge, the combination of charging data collected for residential and commercial vehicles, logging of driving patterns and monitoring of public charging stations constitutes one of the largest trials to date in Great Britain.

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 generation and technologies such as nuclear and carbon capture and storage. A transport sector based on EVs would be characterised by significant flexibility in terms of when the vehicles charge, creating opportunities for utilising more efficient charging strategies to optimise electricity generation and enhance the efficient usage of network capacity. Unlike conventional vehicles, EVs offer their users the convenience of charging at home without the physical presence of the driver, although this comes at the cost of lower driving range and longer charging times.

The EV data collected in the LCL trial covered three broad areas: (i) metered EV charging data for 72 residential and 54 commercial charging points; (ii) data on charging events collected at 491 public charging points; and (iii) vehicle logger data capturing driving and charging behaviour for 30 EVs. Key information recorded included active power for charging, timing and duration of charging events and the energy required by EVs during charge events.

Residential EV trials have confirmed the assumptions made in previous studies that uncontrolled EV charging results in high peaks that broadly coincide with the existing system peak demand, creating additional stress for the electricity system infrastructure. This occurred even in some cases when a tariff incentive was in place with the customer. The highest demand for residential EV charging is recorded between 6pm and midnight, with very low demand during night and early morning hours. The charging demand per vehicle, averaged across all days covered by the trial is about 3.5 kWh, which corresponds to around 17.5 km in distance travelled. This is slightly lower than assumed in previous studies for a nationally representative sample, which could be expected given that LCL EV trials took place in an urban environment characterised by shorter driving distances.

A major share of EV charging demand for the monitored residential and commercial vehicles was met through home charging posts for residential i.e. office charging points for commercial participants. Only 13 to 16% of charging events occurred at charging points other than these. The average observed duration of charging events was about 2 hours for residential and 3 hours for commercial vehicles, with only a small number of events taking
more than 5-6 hours. The median distance associated with a single journey undertaken by both residential and commercial EVs and recorded by data loggers was around 3.5 km, while 95% of trips were shorter than 25 km and 20 km for the two groups, respectively.

A very regular diversity effect is observed for the charging demand of the residential EV sample, with diversified peak demand per vehicle at about 25% of the peak demand for an individual vehicle. This means that for a population of EVs of the size of the residential sample, each with a maximum charging power of 3.6 kW, the diversified peak to be used for calculating aggregate EV demand would be only 0.9 kW. For larger numbers of EVs the diversity factor converges to around 20%, while for a low number of vehicles connected to a common supply point (i.e. less than 10) this factor increases to 63% or more. Diversity considerations provide an important input into the network planning process.

Case studies conducted in this report based on vehicle logger data for residential EVs identified a significant potential for smart EV charging to support peak demand management, without affecting the capability of EV users to make their intended journeys. This suggests that implementing smart charging strategies will be crucial to ensure an efficient integration of EV demand into the existing electricity systems.

Energy requirements for commercial EVs are found to diverge significantly depending on the vehicle use. For pool and company vehicles the energy requirement was about 2.5 times lower than for residential, with about 1.4 kWh of electricity required daily (sufficient to cover about 7 km). Delivery fleets on the other hand required about 14 kWh per charging point and per day. The charging profile of the former subgroup peaks around 10am and then gradually tails off towards the end of business hours (6pm), while the charging patterns of delivery vans display a rapid increase in demand from virtually zero to about 2 kW per charging point between 3pm and 6pm on workdays. Despite the lower sample size in the pool and company car group (there were eventually only 16 vehicles with charging power data), there is again considerable diversity observed with respect to the peak demand observed – diversified peak per EV was about 30% of individual vehicle peak demand. The diversity factor for the 10 delivery vehicles included in the trial was much higher, about 86%, due to the high coincidence of charging across different charging points driven by shift work. This proves that the connection of different types of commercial users and their impact on planning network infrastructure will need to be considered taking into account their specific charging profiles, energy requirements and diversity characteristics.

The programme monitored all of the available public charging stations in the Source London network when it commenced in 2013 (the number at the end of May 2014 stood at 1,408). It was found however that a significant number had zero charging events and so were discounted from the analysis. The data suggest that public stations were used rather infrequently, with great variations in charging duration and energy. The median usage frequency for a charging station was 5.5 times per month, and median number of charging events at these stations per EV was 3 over the trial period (16 months). Users generally relied on public charging stations for a small fraction of their daily distances travelled (median daily energy per EV was equivalent to 0.4 km per day). Peak electricity demand averaged across all stations was 0.1 kW, and the most intensive usage occurred between
12pm and 4pm. Energy demand during weekends was about 35% lower than on workdays. 

Whilst public charging infrastructure is often quoted as a barrier or a pre-requisite for the uptake of electric vehicles, it is not yet being heavily used by existing early adopters in the London area.

Evidence on the use of EVs by trial participants represents an important breakthrough in terms of understanding the requirements of EV users, as this type of data has not been available previously in this form and on this scale. The trials carried out confirmed and verified the EV demand models previously used by the authors of this report that were based on nationally representative driving statistics for conventional vehicles. These models, calibrated using the LCL EV trial data, will therefore continue to be used in the later stages of the LCL project to investigate the opportunities for more efficient distribution network planning with smart EV charging, in particular in the LCL Report D4 “Design of smart distribution networks”.

Trial data analysis has shown that the shape of the additional EV charging demand will depend on several critical factors, such as the number of vehicles involved, user type and day of the week. Understanding the expectations regarding the future uptake of EVs in a given distribution network therefore seems critical in order to appropriately plan for the projected demand increase in existing residential households and to meet new connections associated with public charge posts and organisations converting their fleet to electric vehicles. Updating the demand forecasts based on the expected EV uptake will thus facilitate making informed and appropriate infrastructure reinforcement decisions. The analysis carried out in this report can also provide a basis for assessing the diversity of aggregate EV demand depending on the expected evolution of EV penetration.

Given the potential to use the flexibility of EV demand to support network management, as illustrated in the case studies in the report, the value of different smart charging control approaches should be thoroughly understood and taken into consideration in distribution network operation and planning, along with the traditional reinforcement solutions available to network operators. Preliminary analysis presented in this report shows a significant potential of smart EV charging to deliver savings in distribution infrastructure investment.

The analysis based on evidence gathered in the LCL EV trials has demonstrated there are significant opportunities for adopting smart charging approaches in order to ensure an efficient integration of electrified road transport, but also indicates segments in which this will not be needed for some time to come, such as the low-utilised public charging points. Potential benefits from smart charging schemes, backed by a substantial body of trial data, indicate that their implementation will be vital for enabling an efficient deployment of a high number of EVs in distribution grids.
<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>AC</td>
<td>Air Conditioning</td>
</tr>
<tr>
<td>CNO</td>
<td>Charging Network Operator</td>
</tr>
<tr>
<td>CP</td>
<td>Charging Point</td>
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<tr>
<td>DNO</td>
<td>Distribution Network Operator</td>
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<tr>
<td>DSR</td>
<td>Demand-Side Response</td>
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<tr>
<td>EV</td>
<td>Electric Vehicle</td>
</tr>
<tr>
<td>FP7</td>
<td>7th Framework Programme (European Commission)</td>
</tr>
<tr>
<td>ICT</td>
<td>Information and Communication Technology</td>
</tr>
<tr>
<td>LCL</td>
<td>Low Carbon London</td>
</tr>
<tr>
<td>ODS</td>
<td>Operational Data Store (database containing LCL network and measurement data)</td>
</tr>
<tr>
<td>RFID</td>
<td>Radio-Frequency IDentification</td>
</tr>
<tr>
<td>SoC</td>
<td>State of Charge</td>
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<tr>
<td>TFL</td>
<td>Transport for London</td>
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<tr>
<td>TOU</td>
<td>Time of Use</td>
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<tr>
<td>THD</td>
<td>Total Harmonic Distortion</td>
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1. Introduction

1.1. Objectives and scope
This report 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 Source London network is run by Transport for London and represents a city-wide network of charging points within the Greater London Authority’s catchment area.

The key objective of the analysis presented in the report is to use the extensive volume of EV trial data collected in the project 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 facilitate network planning to accommodate the additional load.

In addition to establishing the characteristics of the EV demand where charging behaviour is predominantly user-led, the objective of this report is also to assess the opportunities for smart charging of EVs. This can provide grid support while respecting the constraints with respect to the EV users’ journey patterns and their requirement to have their vehicles sufficiently charged.1

In that context, the report aims to provide answers to the following research questions:

- What are the expected average and worst-case EV charging profiles that are relevant for distribution network planning?
- How do the charging profiles change with the number of EVs observed?
- What is the impact of day of week, season and user type on EV charging patterns?
- To what extent can EV demand be shifted in time to support grid management, while respecting the users’ requirements?

1.2. Context
Electrification of road transport is becoming increasingly important in the context of reducing carbon emissions from the energy sector, accompanied with an increased share of renewable and other low-carbon electricity generation.

Based on typical vehicle usage patterns and specific features of the EV technology, EV loads appear to be particularly well placed to support system operation, for the following reasons:

1 The focus of this report is on the impact of charging on distribution network (DNO perspective) it does not consider the potential for injecting energy from EV batteries back into the grid, i.e. Vehicles to Grid (V2G) applications.
The additional energy requirements for EV charging are relatively modest compared to the electricity demand already existing in the system. Even if the entire UK light vehicle fleet switches to electricity, the total demand would not exceed 15% of annual GB electricity system demand. On the other hand the power requirements for charging in the case without any charging management may increase the total system peak demand by as much as 50% [1].

Driving times generally associated with the majority of small passenger vehicles are relatively short. As indicated in Figure 1, plotted based on the representative journey database for the UK, the proportion of non-stationary vehicles only occasionally exceeds 20% during a typical day.\(^2\)

Given that vehicles are stationary for most of the day at locations where they could potentially be charged (homes, offices), there is much more flexibility in terms of delivering charging energy than in the case of re-fuelling conventional vehicles. This provides the potential for more controllable charging without the direct involvement of the user, while respecting the user’s journey requirements.

Given that EV batteries have relatively high power ratings as well as capacities in the order of tens of kWh, they could eventually be used as flexible demand resource to enable more efficient system operation.

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 [2],[3]. A significant penetration of EVs in a system characterised by a high penetration of intermittent renewable resources may provide

\(^2\) The figure is based on Department of Transport’s National Transport Survey for the (conventional) light vehicle fleet in the UK [4]. This data was used by the authors in previous studies analysing the impact of electrified transport on the power system such as [8].
significant benefits to the system by treating EV charging load as flexible demand, which can be shifted towards periods of surplus energy [5],[6]. Benefits of smart EV charging for a more efficient integration of wind generation in the future UK system are explored in detail in [7].

Similarly, the FP7 Grid-for-Vehicles project addressed the issue of efficient grid integration of large penetrations of EVs [1], while the report prepared for the Energy Networks Association in 2010 specifically addressed the potential for smart EV charging to facilitate more efficient distribution network investment through avoiding reinforcements due to EV deployment [8]. One of the aims of the work carried out by Low Carbon London has been to validate the assumptions made in the previous analysis prepared for the Energy Network Association, by replacing assumptions with real trial data.

The key issue for an efficient integration of electrified transport from a DNO perspective is the ability to support charging network operators and property developers as they build the infrastructure for electric vehicles, ahead of and to encourage a major uptake, as cost-effectively as possible. Once a significant EV uptake commences, DNOs will need to be able to support the additional demand on the system, and the cost of this support will depend not only on the level of new EV demand but also on the uptake of smart charging strategies.

1.3. Other EV trials
A number of EV trials and demonstration projects have been launched in recent years both in the UK and in Europe. One of the longest running ones was the Switch EV project³, where 44 vehicles were leased to individuals and organisations in the North East of England between May 2010 and May 2013. The project looked at both the infrastructure usage and technical aspects of EV driving, as well as the user perspective and the perception of EVs [9].

At the European level, the FP7 project Green eMotion has been launched in 2011, with the objective of demonstrating a pan-European viability of the electromobility concept through demonstrations in Ireland, Italy, Denmark, Sweden, Germany, Austria and France [10]. The project involves more than 40 partners from around Europe, and addresses a number of aspects related to a Europe-wide mass rollout of EVs, such as: interoperability, roaming and ICT solutions, grid impact, charging infrastructure, vehicle testing, standardisation, economic and environmental considerations, consumer preferences and behaviour, and policy recommendations. Demonstrations commenced in 2012 and are expected to finish in 2015.

Although EVs have gained wide recognition as a critical element of the decarbonisation agenda, there is limited (although rapidly growing) body of evidence on actual EV usage and charging patterns as opposed to those associated with conventional vehicles. 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 electricity system and the opportunities for deploying alternative and more efficient charging strategies. The data collected in LCL EV trials,

³ http://www.switchev.co.uk/.
covering a period of more than a year, therefore provides a crucial input into understanding the impact of EVs both at the level of local distribution network as well as system-wide. 

In particular, the evidence collected on actual EV usage patterns will be used in this report as an input to evaluate the potential contribution of smart EV charging to more efficient network management. Among other findings, it confirms charging behaviours such as regular top-up charges and plugging in directly after use that could only be assumed or ‘suspected’ prior to this work. This is in contrast to previous assessments of this kind (e.g. [8]) that made assumptions on EV usage based on the driving patterns associated with conventional vehicles. This further stresses the importance of quantitative evidence gathered in LCL EV trials.
2. 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 on driving, charging and parking

This section provides a description of the three datasets, including the number of EVs involved and duration of data collection activity.

2.1. EV charging data

The 72 residential customers fell into two categories: 47 existing EV users who had an EV before the trial started; and 25 new users that had EVs leased to them on a short-term (1-year) arrangement. On the commercial EV trial, 54 customers fell into several categories: a delivery fleet; a car pool owned by Transport for London and typically used for reactive call-outs; and a variety of additional leases to new users as company cars. Across the data sets, a variety of EV models were present. 25 new residential users were all leased Nissan Leafs, while the vehicles already owned by the remaining 47 participants included a mix of Nissan, Smart, Chevrolet, Toyota, Citroen, Mitsubishi and Reva models.

The data from remote meters installed at dedicated charging stations have been stored in the LCL ODS database. Each meter recorded the following relevant information in 10-minute resolution:

- Reading date and time
- Active and reactive power
- Voltage and current

Analysing data on a 10-minute resolution is vital to understand diversity. Typically, DNOs will both plan and measure on a half-hourly averaged resolution, which disguises the underlying diversity.

For the analysis in this report the active power is used as a crucial input. Table 1 summarises the scope of available active power data collected for the two datasets. Out of the total number of meters, only a subset had any active power data associated with them in the database (row “Meters with active power measurements”), while some of those only contained zero values for measured active power. This was due to a number of reasons such as participants not using the EVs during the trial period, participants having sold their EVs,

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4 Other parameters such as Total Harmonic Distortion (THD) were also recorded, but are not analysed in this report. This and other power quality issues are addressed in detail in the companion LCL report B3 Error! Reference source not found.
5 The snapshot of the databases was taken on 24 April 2014.
data communication issues with the meter etc. The remaining meters with non-zero measurements included 54 meters in residential and 26 in the commercial group, respectively. The volume of data collected per user was equivalent to 302 and 255 days of continuous data for residential and commercial participants, respectively.

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

<table>
<thead>
<tr>
<th></th>
<th>Residential</th>
<th>Commercial</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of meters</td>
<td>72</td>
<td>54</td>
</tr>
<tr>
<td>Meters with active power measurements</td>
<td>56</td>
<td>40</td>
</tr>
<tr>
<td>Meters with non-zero active power measurements</td>
<td>54</td>
<td>26</td>
</tr>
<tr>
<td>Total number of active power measurements</td>
<td>2.35m</td>
<td>0.95m</td>
</tr>
<tr>
<td>Equivalent days per EV</td>
<td>302</td>
<td>255</td>
</tr>
<tr>
<td>Start date</td>
<td>2 April 2013</td>
<td>19 February 2013</td>
</tr>
</tbody>
</table>

The coverage of charging data was not continuous for all meters involved. As illustrated in Figure 2 for both samples (after filtering to 54 i.e. 26 participants), where each horizontal line corresponds to an individual meter, most residential meters start recording at the start of the trial i.e. beginning of April 2013, and there are also many that start in mid-May 2013. Most residential participants’ meters were still active at the end of April 2014, when the most recent snapshot of the database was taken (although a number of them stopped recording earlier for a variety of reasons mentioned earlier, such as e.g. participants selling their vehicles). Commercial participants are further divided into two subgroups depending on the meter type (1-phase or 3-phase). This distinction was due to the fact that only electric delivery vans used by UPS connected to 3-phase meters during the commercial trial, and given their very specific charging patterns and energy requirements, their analysis is presented separately from the rest of the commercial participants throughout the report. Some of these delivery vans started recording charging data already in February 2013, while most other commercial participants joined the trial in early April 2013. The agreement with commercial users envisaged the termination of trial at the end of 2013, which did occur for many of them, although some continued monitoring their charging data well into 2014.

Figure 2. Time covered by charging data for 54 residential (left) and 26 commercial (right) EV fleets

Figure 2 also reveals certain gaps in data covered by the trials, most notably during the period of about two weeks in the second half of July 2013, when only 3-4 residential and a few commercial meters seemed to have continued recording as the result of remote meter
profile updates. These data gaps are addressed in the analysis as detailed in the next sections.

2.2. Public charging points data

Data associated with public charging points included in the Source London programme were collected as part of the EV trial. Source London is run by Transport for London (TfL) and have contracted with four different Charging Network Operators (CNOs): ChargeMaster, PodPoint, Elektromotive and CPMS. The Low Carbon London project negotiated data-sharing agreement with all four CNOs, with the support of Transport for London, in order for this data to be shared with LCL. The structure of the information available is different than for the residential and commercial trials as no continuous recording took place. The charging events were instead logged when they happened, recording the following information for each charging event:

- Timestamps for charging start and completion
- Energy transferred during charging event
- CNO ID, charging point ID and plug ID
- Vehicle identification (RFID)

As of 29 May 2014, Source London network comprised of 1,408 charging points. Out of those, the public stations data included in the ODS contained 22,350 events for 491 stations and 1,656 unique EVs. The period covered is from 1 October 2012 to 6 February 2014. A great number of events (4,780) had a zero energy associated with them, and further 475 had a consumption below 0.1 kWh. If those are discarded from the dataset, 391 charging stations remain and their time coverage disaggregated by CNO is depicted in Figure 3, where each line goes from the first to the last event recorded for a given charging station. It is evident that there is great variety in the periods covered by charging events for different charging stations. The analysis conducted in later sections will be based on this reduced charging event dataset.
2.3. Vehicle logger data

As part of the EV trial, a subset of EVs has been equipped with detailed journey data loggers, and the corresponding data have been made available for analysis. The data entries in the database 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 (the list is not exhaustive):

- Vehicle ID
- Start and end times
- Start and end address
- Distance travelled
- Average and maximum speed
- Start and end battery State of Charge (SoC)
- Energy transferred during charge segment
- A number of other parameters: state of heating/AC, time spent in different gears etc.

The logger data covered 22 residential and 8 commercial vehicles. Their time coverage is illustrated in Figure 4. Most residential vehicles started recording in mid-May 2013, whereas commercial participants generally started the trial in early July 2013. Most of these were still active when the most recent snapshot was taken at the end of April 2014.
Although there are no gaps in data once the records begin, i.e. the D/P/C events in the database are contiguous, there are evidently periods where the activity has not been tracked, characterised by very long events taking weeks or months. This was generally caused by technical issues i.e. the loggers interfering with 12 V batteries, in which cases the loggers were disconnected while the issue was investigated.

Ten of the new residential EV users recruited by the project also had data loggers installed to analyse their journey patterns, in addition to having their charging data collected via remote meters. On the other hand, there were no commercial vehicles for which both the logger data and metered charging data were recorded.
3. EV charging analysis

The analysis presented in this section will focus on identifying the key features of EV charging demand, in particular the energy requirement for EV charging, temporal variations in charging demand and statistical diversity of demand as function of the number of EVs involved. The section is divided into descriptions of residential charging demand, commercial charging demand and the usage of public charging points.

3.1. Residential EV charging demand

As discussed earlier, the residential EV charging data sample included 54 vehicles that have been monitored over a period of more than a year. The initial analysis of their 10-minute charging profiles revealed that most vehicles charged at 3.7 kW (i.e. 16 A), although both higher (up to 7.4 kW) and lower (1.7 kW) maximum charging powers are also observed. Figure 5 illustrates a typical charging demand pattern for an individual vehicle with a 3.7 kW charging post. At first glance, there is not much daily or weekly regularity in the charging pattern, suggesting it may be difficult to forecast the demand profile for a single vehicle.

![Figure 5. Charging profile for a single residential vehicle during the trial period](image)

Most charging events recorded in the EVD database lasted for a few hours. A typical residential charging event is depicted in Figure 6. This is a charging profile for a single charging event for one selected EV from the residential EV trial. This charging event is considered to be typical with respect to the power and time involved, and is used to illustrate what a charging event looks like for an individual vehicle.

The event takes about 2.5 hours, during which 6.6 kWh is consumed from the grid. Another phenomenon that is visible in Figure 6 is the gradual decrease of charging power (at about 0.12 kW per minute) towards the end of charging. This only occurs when the EV battery is being charged to its full capacity, and is most likely caused by the control actions of the battery management system. If charging is terminated before the battery is full on the other hand, the charging power drops to zero instantaneously.
3.1.1. Data gaps

As discussed in Section 2.1, the charging data available for the 54 residential EVs generally does not continuously cover the entire length of the trial period. A significant gap in data is observed for the 2-week period in the second half of July 2013, as well as for several other days. This is further illustrated in Figure 7, where the number of vehicles with recorded data has been plotted for each day of the residential EV trial period.

In order to avoid the undesired impact of data with only a small number of vehicles on the characteristics of the entire population i.e. to maintain a certain level of EV load diversity, the original dataset has been reduced by discarding the 23 days in which the number of EVs with charging data dropped below 35 (roughly about two thirds of the total number of 54 vehicles). This threshold is indicated by a red line in Figure 7. After discarding the days with low EV data coverage, the resulting coverage is depicted in Figure 8. The average number of EVs with charging data in the reduced dataset is 44, i.e. about the same size as the trials undertaken by the Switch EV project in North East England, mentioned in Section 1.3.
3.1.2. Average charging profiles

In the first step the average charging profiles for the residential EV sample have been found by computing the average values for each of the 144 10-minute intervals during the day. The averages have been 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 that contained a sufficient level of charging data. The results are presented in Figure 9.

Peak demand for residential EV charging occurs around 9pm in the evening. The bulk of charging energy requirements is generally supplied between 6pm and midnight. As expected, the charging demand on workdays is higher than during weekends; average daily requirement is 3.68 kWh for workdays and 3.09 kWh for the weekend. It is further interesting to note that the evening demand for charging is higher on Sunday than on Saturday, presumably due to the users charging to prepare for the start of the working week. Another notable difference between working days and weekends is that the charging demand over the working week is higher than for weekends in the morning between about 5am and 11am; the situation then reverses between 11am and 5pm, which is when the weekend demand exceeds that of a working day. This can be explained by users being at home for longer and starting their activities later during the weekends.
Average daily requirements for different days, as well as maximum values of average demand per EV are summarised in Table 2.

<table>
<thead>
<tr>
<th>Day type</th>
<th>Energy requirement for charging (kWh)</th>
<th>Peak average demand (kW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All days</td>
<td>3.52</td>
<td>0.30</td>
</tr>
<tr>
<td>Workdays</td>
<td>3.68</td>
<td>0.33</td>
</tr>
<tr>
<td>Weekend</td>
<td>3.09</td>
<td>0.23</td>
</tr>
<tr>
<td>Monday</td>
<td>3.33</td>
<td>0.34</td>
</tr>
<tr>
<td>Tuesday</td>
<td>3.84</td>
<td>0.35</td>
</tr>
<tr>
<td>Wednesday</td>
<td>3.57</td>
<td>0.30</td>
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<tr>
<td>Thursday</td>
<td>3.80</td>
<td>0.38</td>
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<td>Friday</td>
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<tr>
<td>Saturday</td>
<td>2.96</td>
<td>0.22</td>
</tr>
<tr>
<td>Sunday</td>
<td>3.22</td>
<td>0.28</td>
</tr>
</tbody>
</table>

Peak value for average demand per EV is around 0.3 kW for an average day. This increases to 0.33 kW for an average workday, while the highest maximum value of demand per EV is observed on Thursdays at 0.38 kW. For comparison, all these values are about an order of magnitude less than the maximum charging power of an individual vehicle (3.7 kW) for this number of residential EV users. As a further reference point, the diversified peak demand of residential customers in the UK is in the order of 1 kW, or about three times the diversified charging peak (although the two peaks do not necessarily occur simultaneously).

3.1.3. Worst-case charging profiles
Average charging demand is a useful indicator for the typical fluctuations in EV charging demand, however in order to inform the distribution network planning process it is necessary to know the maximum aggregate EV demand that can be reasonably expected, i.e. the demand level which is only exceeded with a very small probability. For this purpose, the maximum value of charging demand per EV was found across the trial period for each of the 144 10-minute intervals of the day. Unlike the average profile for a given 10-minute interval (the same as in Figure 9), which is calculated as the average charging power across all EVs and across all instances of this 10-minute interval over the trial period, the maximum profile is obtained by finding the highest value of average charging power per EV across all instances of a given 10-minute period. The resulting profile is compared to the average charging profile as shown in Figure 10.
The maximum demand per EV recorded in a single 10-minute interval is 0.88 kW, which is about 3 times higher than the maximum value of demand per EV averaged over all observations for a given interval during the entire trial period. The profile constructed from maximum values across the trial period can be considered as a “worst-case” scenario for the analysed residential EV sample. The value of 0.88 kW can also be interpreted as the diversified peak demand for the sample of 54 residential EVs. The non-diversified maximum demand per EV would be about 3.5 kW (a combination of mostly 3.7 kW chargers, a few 7.4 kW chargers, and a few EVs with lower charger ratings), which suggests that the diversity factor for EV demand i.e. the ratio between diversified and non-diversified peak demand would be about 25%.

In order to further explore the statistical properties of the residential EV demand, Figure 11 quantifies additional metrics for EV charging profiles relevant for network planning. Different levels of probability associated with these profiles can be linked to different levels of reliability that may need to be ensured in various networks. In addition to the average and maximum (worst-case) charging profile depicted in Figure 10, the following statistically derived profiles are computed and included in Figure 11:

- 95th percentile for all observations in each interval
- 99th percentile for all observations in each interval
- Sum of average charging profile and 2 standard deviations in each interval
- Sum of average charging profile and 3 standard deviations in each interval

---

6 As discussed in Section 3.1.1, given that not all vehicles had their charging data monitored over the entire trial period, the number of simultaneously monitored home charging points for the sample of 54 EVs varied around the value of 44.
It can be observed that although the measurements in each interval are generally not normally distributed, the profiles reflect fairly well the expected probability levels for normally distributed variables. The profiles corresponding to the 95\textsuperscript{th} percentile and average value plus 2 standard deviations are very similar, with the peak of around 0.6 kW. The profile for the 99\textsuperscript{th} percentile has a peak of 0.76 kW, as it does not include the most extreme values recorded in the maximum demand profile that form the tails of the distribution of observations. Finally, the average profile plus 3 standard deviations, which would exceed about 99.9\% of observations in a normal distribution, generally exceeds even the maximum demand profile per EV, resulting in the highest diversified peak demand of 1.07 kW. This would still imply a diversity factor of around 30\% as relevant for the residential EV sample of this size.

Importantly, comparing the maximum diversified demand with the average demand indicates that the diversity factor is reasonably stable throughout the day, without any particular times in the day when the two curves diverge more than at other times. As such, it is appropriate to rely on a single diversity factor. From this analysis, a prudent conservative approach to assessing the maximum diversified peak of large number of EVs would be to use average profile and add 3 standard deviations, which would lead to a figure of about 1 kW (the largest peak observed in the trial is 0.88 kW).

3.1.4. Diversity of residential EV demand
This section analyses in more detail the diversity of residential EV demand that can be inferred from the trial data. The concept of diversity of electricity demand has been in use for network planning for a long time. In the context of increasing number of EVs being connected to distribution networks, it is important to estimate how their diversified peak demand...
increases with lower EV population sizes. For that purpose, the maximum and average demand profiles have been quantified for the following sample sizes:

- 10 EVs
- 21 EVs
- 32 EVs
- 43 EVs
- 54 EVs (full sample)

For each subsample size 10 vehicle groups were successively generated by randomly drawing vehicles from the full sample of 54 EVs. The examples of maximum and average charging profiles per EV for different subsample sizes are illustrated in Figure 12. There is a clear trend towards increasing maximum peak demand for smaller sample sizes.

![Figure 12. Maximum and average charging profiles for different subsample sizes of residential EVs](image)

The functional relationship between the diversity factor (ratio between diversified and non-diversified peak demand) and the sample size is depicted in Figure 13 (the theoretical 100% diversity factor for a single EV is also added for reference). For each subsample size the mean, maximum and minimum values of diversity factor are depicted across all 10 random draws.

---

7 Again, as pointed out in Section 3.1.1, due to less than 100% time coverage for individual residential users during the trial, the average number of EVs monitored simultaneously at any given point in time is smaller than the full sample (or subsample) size.
The results suggest a very regular relationship between the diversity factor and sample size, with a steady decline with increasing sample sizes. The value of diversity factor in this case seems to asymptotically approach the level of around 20% for very large sample sizes. It is further noted that the uncertainty around the mean value decreases with higher sample sizes, as expected. Additional calculations (not presented here) confirmed the robustness of the diversity factor curve shown in Figure 13, as there were no significant changes in this curve for a larger number of random draws in each subsample.

This characteristic represents a critical input into network planning, as the additional requirements for network infrastructure capacity will be driven by the aggregate charging demand of new EV loads. The diversity factor provides an important link between the expected number of EVs in the network and the expected increase in peak demand that needs to be supplied by the network.

The diversity of EV demand is expected to have a great importance for planning LV substations and even more so for LV feeders where clustering of EVs could potentially occur. A further reduction in diversity may be observed in networks with unbalanced EV loads, i.e. if the distribution of EVs across the three phases is asymmetrical. In such cases the diversity factors identified above will need to be adjusted (i.e. increased) to account for the effective diversity seen by the 3-phase system.

The diversity factors calculated here are expected to remain fairly robust in the future. On one hand, if there is a shift in EV technology towards larger chargers and larger battery packs, the charging duration and consequently the diversity factor are not likely to change significantly. On other hand, with possible improvements in battery and charger efficiency, the charging duration is likely to become shorter. However, this would not affect the evening charging peak, when most vehicles are expected to connect, but rather the rate of demand drop towards later evening hours.

Figure 13. Diversity factor for different subsample sizes of residential EVs
3.1.5. Daily energy requirements

Vehicles in the residential EV trial exhibited great variation in the charging energy required to support their journeys. This is a direct consequence of different mobility requirements i.e. different daily distances. There was also significant variation for individual vehicles across different days.

Figure 14 illustrates the variation in average daily requirements for vehicles in the residential sample. The average charging demand per day was 3.57 kWh, but this varied greatly between 0.13 kWh per day for one vehicle to 11.35 kWh for another.

![Figure 14. Distribution of daily energy requirements for the residential EV sample](image)

A subgroup of 9 most intensive EV users required more than 7 kWh per day, which is broadly equivalent to daily distances of 35 to 53 km.

3.1.6. Frequency of charging

Participants in the residential EV trial also differed greatly with respect to the frequency of charging their EVs. Figure 15 quantifies the number of days with and without charging activity for the users in the residential EV trial. The average daily energy requirement for each vehicle and for the whole population is also plotted for comparison.

![Figure 15. Number of days with and without charging activity for individual users in the residential EV sample](image)
Depending on the intensity of EV usage, percentage of days without any charging varies greatly within the sample: between 2% and 99% (the average value is 50%). As discussed earlier, not all vehicles have the data recorded for the same number of days; this is why the total number of days depicted in Figure 15 varied from one vehicle to another.

Figure 15 does not contain the information on how much time the vehicles actually spent charging. The share of time used for charging is therefore depicted in Figure 16 for all residential EVs.

![Figure 16. Time used for charging of individual EVs in the residential sample](image)

According to the charging data, residential EVs spent on average 7.8% of time charging (or just below 2 hours per day), which varied between 0.2% and 32.7% for individual vehicles. In context, though, this is significantly longer than any other existing non-heating loads in the home, such as power showers. Although this does not mean that the vehicles are available for demand shifting for the rest of the time, there seems to be considerable potential for smart charging of residential EVs. However, to have a full understanding of the potential flexibility of EV demand, parking and driving times need to be considered. This analysis is carried out in Section 4.6 based on detailed vehicle logger data.

3.1.7. Duration of charging events

Based on the data in the EVD database, and after ignoring the readings with very low value, it was possible to identify 9,909 distinct charging events in the database for the sample of 54 residential vehicles. These events differed greatly in terms of their duration. This is illustrated in Figure 17, where the frequency distribution of charging duration is plotted for residential participants. Key statistical parameters of charging duration are further presented in Table 3. It has to be noted that due to the time resolution of charging power
readings (10 minute), the smallest multiple of charging durations inferred from the database was also 10 minutes.

![Charging duration frequency distribution](image)

**Figure 17. Frequency distribution of charging event duration for residential EVs**

**Table 3. Statistical parameters of charging duration for residential EVs**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>1h 57min</td>
</tr>
<tr>
<td>Median</td>
<td>1h 30min</td>
</tr>
<tr>
<td>Minimum</td>
<td>10min</td>
</tr>
<tr>
<td>Maximum</td>
<td>11h 30min</td>
</tr>
<tr>
<td>5th percentile</td>
<td>10min</td>
</tr>
<tr>
<td>95th percentile</td>
<td>4h 50min</td>
</tr>
</tbody>
</table>

The data suggest that more than 95% of charging events took less than 5 hours. A general observation is that events of shorter durations are more frequent, with two notable clusters of events for durations of about 30 minutes and about 90 minutes. Given that the battery of a Nissan Leaf (24 kWh), which was the most represented EV model in the residential trial, takes about 6 hours to charge from a very low level of 20% to full charge at a typical charging power of 3.7 kW, these results reflect the fact that only a few users charged their battery when they reached a very low SoC; most users opted for charging the battery at an intermediate level of SoC.

The results also suggest that a great majority of charging events can be rather easily performed during the night, which implies there is a significant room for deploying flexible charging schemes i.e. shifting charging demand towards the late evening and night hours.

### 3.2. Commercial EV charging demand

The analysis presented in this section is based on the commercial EV charging data. The size of the commercial EV population that contained non-zero charging profiles is 26, comparably smaller than for the residential sample. This limits somewhat the scope of the analysis, in particular the assessment of the diversity of EV demand for different subsample sizes, but it is also less relevant given the variety of activities within the commercial sample. Nevertheless, the key parameters characterising the commercial EV charging demand are quantified and studied in the remainder of the section.
Similar to the residential participants, 16 of the 26 commercial charging points had a single-phase connection, with most of these vehicles charging at 3.7 kW (i.e. 16 A), although both higher (up to 7.3 kW) and lower (1.2 kW) maximum charging powers are also observed. Characteristic charging profiles are also similar as in the residential sample, as the type of vehicles and the battery management systems involved were similar.

The remaining 10 commercial vehicles on the other hand had a 3-phase connection, also reflected in higher maximum charging power (up to 14 kW). Vehicles using these charging points were UPS delivery vans, and when presenting the results of the analysis of the commercial EV charging, they will be characterised as a separate subgroup.

3.2.1. Data gaps
The discussion of the data coverage in Section 2.1 indicated there are missing data for some periods and some vehicles in the commercial EV sample. This is further illustrated in Figure 18, which shows that the number of EVs represented in the commercial sample over the course of the trial. Starting from early April 2013 the number of vehicles with recorded data reached 20 and stayed above this value until late November 2013 (with the exception of a short period during July 2013 when there was very little data due to technical issues mentioned earlier).

![Figure 18. Number of commercial vehicles with recorded charging data over the trial period](image)

Similarly to the residential EV charging analysis, a coverage threshold of 20 vehicles is introduced in order to avoid unrepresentative results driven by periods with a low number of observations. All days when the number of EVs with charging data drops below 20 were not included in the analysis of average and maximum charging profiles. After this reduction, the average number of EVs included in the data over the course of the trial period was 22.4.

---

8 Selecting this threshold represents a compromise between having year-round data coverage and having a sufficient number of EVs represented at any given point in time (i.e. ensuring diversity).
3.2.2. Average charging profiles

Following earlier discussion, due to the heterogeneity of commercial trial participants, their charging profiles are separated into two subgroups:

- Single-phase users: car pool, company cars
- 3-phase users: electric delivery vans

Average daily requirements for different days, as well as maximum values of average demand per user for both subgroups in the commercial fleet are summarised in Table 4.

<table>
<thead>
<tr>
<th>Day type</th>
<th>Energy requirement for charging (kWh)</th>
<th>Peak average demand (kW)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1-phase</td>
<td>3-phase</td>
</tr>
<tr>
<td>All days</td>
<td>1.20</td>
<td>15.4</td>
</tr>
<tr>
<td>Workdays</td>
<td>1.53</td>
<td>17.4</td>
</tr>
<tr>
<td>Weekend</td>
<td>0.40</td>
<td>10.4</td>
</tr>
<tr>
<td>Monday</td>
<td>1.23</td>
<td>14.2</td>
</tr>
<tr>
<td>Tuesday</td>
<td>1.39</td>
<td>21.1</td>
</tr>
<tr>
<td>Wednesday</td>
<td>1.50</td>
<td>19.2</td>
</tr>
<tr>
<td>Thursday</td>
<td>2.10</td>
<td>20.3</td>
</tr>
<tr>
<td>Friday</td>
<td>1.42</td>
<td>12.0</td>
</tr>
<tr>
<td>Saturday</td>
<td>0.38</td>
<td>18.3</td>
</tr>
<tr>
<td>Sunday</td>
<td>0.41</td>
<td>2.5</td>
</tr>
</tbody>
</table>

The average charging profiles for the single-phase commercial EV users, found by computing the average values for each of the 144 unit intervals during the day, are presented in Figure 19.

Unlike the residential EV charging demand, the peak demand for commercial vehicles connected to single-phase meters occurred around 10am in the morning. The bulk of charging energy requirements is generally supplied between 8am and 8pm. During workdays, secondary peaks in charging demand can be observed around 5pm. This is broadly
consistent with the expected use of pool vehicles and company cars, where many of them are plugged in in the morning around the start of business hours, while some are gradually connected during the day after they have been used. It appears that very few of these vehicles start charging after 6pm, i.e. that the gradually declining energy required in the evening hours is the result of charging the EVs plugged in before that.

Charging demand during the weekend is very low, which is consistent with the fact that the businesses and offices are closed. Variation among different workdays is also significant (which may also be driven by the small sample size), so that for instance the average peak on Tuesday is 0.24 kW, whereas on Friday it is only about 0.16 kW.

Average daily energy requirement in this subgroup is generally significantly smaller than for residential EVs, suggesting smaller distance requirements. For an average day commercial EVs required 1.45 kWh, while residential users required 3.52 kWh or about 2.5 times more. The equivalent daily distance at that level of consumption is about 7 km.

Figure 20 presents the average charging profiles per user for selected days of the week for the subgroup of commercial users with 3-phase meters, i.e. delivery van fleet (charging profiles for Monday, Wednesday and Thursday were found to be very similar to the Tuesday profile). It is immediately obvious that the energy requirements and the peak demand are an order of magnitude higher than in the first subgroup. This is not surprising given the higher mileage driven by delivery vans and their higher specific consumption per kilometre.

Another very prominent occurrence is the rapid increase of charging demand on weekday afternoons. Charging power per meter increases from virtually zero to about 2 kW between 3pm and 6pm; it remains at a fairly high level afterwards, until charging finishes overnight. Whereas days from Monday to Thursday have very similar charging profiles, evening charging on Friday shows a different pattern, where the demand pick-up in late afternoon is followed by a drop towards 9pm, after which the demand increases again. Demand on Sunday is virtually zero, while on Saturday there appears to be a steady decline from a rather high level, enabling a full charge of van batteries before the start of the next working week.
Coping with the fast increase in demand during late workday afternoons may be challenging for the local distribution network, given that the power levels involved are significantly higher than those of residential users, but also because of the charging demand increase coinciding with the peak in the rest of the system and the lower diversity between the fleet vehicle charging patterns.

### 3.2.3. Worst-case charging profiles

As with the residential EV users, the maximum value of charging demand per commercial charging point was found across the trial period for each of the 144 unit intervals of the day. The distinction is again made between single-phase and 3-phase meters, due to distinctly different characteristics of users connected to those two meter groups. The resulting profiles, compared to the average charging profiles, are depicted in Figure 21.

![Figure 21. Maximum and average charging profiles per EV for commercial users: single-phase users (left) and 3-phase users (right)](image)

Maximum instantaneous average demand for the part of the commercial EV fleet that included pool and company cars was found to be 1.07 kW, about an order of magnitude higher than the maximum average demand per EV of 0.13 kW (the comparable ratio for the residential fleet was about 3). When comparing the diversified peak evaluated in this manner with the non-diversified peak demand for an individual vehicle, the diversity factor for this subgroup is about 29%. This factor is lower than the diversity factor of residential charging demand, which according to Figure 13 would be about 50% for the residential sample of a similar size. This effect is not surprising given the significantly lower overall charging demand of single-phase commercial EVs.

Delivery vans on the other hand were characterised by a much higher diversified peak demand of almost 6 kW per meter (about 4 times the highest value of average demand). We also observe significant synchronicity / coincidence between different vans plugging in, resulting in a rather high diversity factor of 86%.

Given the small sample size and its heterogeneity it did not seem appropriate to generate subsamples of the commercial EV fleet to study the effect of diversity in a way similar to residential EVs.

Additional statistically derived charging profiles for commercial EVs are quantified in Figure 22 and Figure 23 for the single-phase subgroup and for 3-phase meters. Similar to the
residential sample, these profiles include the 95\textsuperscript{th} and 99\textsuperscript{th} percentiles, as well as the sum of average charging profile and 2 or 3 standard deviations.

It is again possible to note the similarity between the 95\textsuperscript{th} percentile profiles and the average plus 2 standard deviations. The maximum charging profiles contain outliers that are not captured by 3 standard deviations from the average, especially in the case of single-phase users where the 9am peak is not captured. The average plus 3 standard deviation profile peaks at 0.57 kW and 5.3 kW for single- and 3-phase users, respectively.

Given the observation that the maximum encountered demand per meter is significantly higher than the average value plus 3 standard deviations (unlike for the residential participants), it is not appropriate to use this measure to estimate the diversified peak for commercial vehicles. This is because of the presence of rare charging events characterised with very high demand levels. The data suggest that great attention has to be given to the type of commercial EV users involved, as the analysis clearly demonstrates great differences in charging patterns and energy requirements between different commercial user categories.
3.2.4. Daily energy requirements
Commercial vehicles also showed great variation in the charging energy driven by different mileages travelled. The overall level of energy demand for single-phase users was several times lower than for the residential EV sample, while the energy required by three-phase users on the other hand was several times higher. Figure 24 illustrates the variation in average daily requirements for a single meter in the commercial sample.

![Figure 24. Distribution of daily energy requirements for the commercial EV sample](image)

The average charging demand per day among the car pool and company car users was 1.45 kWh, but this varied greatly between 0.01 kWh per day for one user to 4.19 kWh for another. Delivery vans on the other hand required a far higher volume of energy per day: 14.2 kWh on average, varying between 0.15 kWh and 33.1 kWh for individual meters.

3.2.5. Frequency of charging
The frequency of EV charging varied significantly among the commercial EV trial participants. Figure 25 quantifies the number of days with and without charging activity for commercial EV users, while also showing the average daily energy requirement for each vehicle.

![Figure 25. Number of days with and without charging activity for individual users in the commercial EV sample](image)

In line with varying intensity of EV usage, percentage of days without any charging varied considerably within the commercial sample, between 0% and 58% for single-phase users.
(the average value was 18%) and between 5% and 82% for 3-phase users (average 44%). The total number of days depicted for some vehicles is shorter due to less charging data being available for those EVs. Several meters in the sample recorded a very low charging demand.

The number of hours used for charging is depicted in Figure 16 for all commercial EVs.

![Figure 26. Time used for charging of individual EVs in the commercial sample](image)

Charging data for single-phase commercial participants suggest they spent on average 2.3% of time charging (or just above 30 minutes per day), which varied between 0% and 10% for individual vehicles. The time used for charging is appropriately lower than for residential EVs, given the difference in energy requirements discussed earlier. This seems to suggest an even broader scope for smart EV charging, provided that constraints related to driving and parking times are respected. Delivery vehicles with 3-phase meters spent much more time charging as the result of their higher energy requirements: between 1% and 37% (17% on average).

Nevertheless, the robustness of these results is arguably smaller than for the residential sample, both because of the smaller number of vehicles in the commercial sample, as well as due to a great diversity of usage patterns that can be expected among the commercial users. There is far less homogeneity among the commercial charging points, as significant differences in usage are likely to be observed between delivery fleets, car sharing pools and company car fleets. Each one of those categories would therefore require a different treatment when considering their impact on the network.

3.2.6. Duration of charging events

In analogy to the residential vehicle database, charging data allowed for identifying 588 charging events in the database for the sample of 16 commercial charge points with single-
phase meters and 1,394 charging events for the 3-phase charging points. The observed frequencies of different charging event durations for both commercial participant subgroups are presented in Figure 27 and Figure 28, and the key parameters of the frequency distributions are given in. In accordance with significantly higher energy requirements for delivery vans, their charging durations are also longer than for single-phase charging point users. While the latter group hardly had any charging events lasting longer than 6 hours, the 3-phase meters saw almost 30% of events taking 6 hours or longer.

Figure 27. Frequency distribution of charging event duration for commercial single-phase charging points

Figure 28. Frequency distribution of charging event duration for commercial 3-phase charging points

Due to a large number of charging events lasting 10 minutes or less, these have been removed before calculating the frequency distribution in Figure 28.
Table 5. Statistical parameters of charging duration for commercial EVs

<table>
<thead>
<tr>
<th></th>
<th>1-phase</th>
<th>3-phase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>2h 59min</td>
<td>3h 34min</td>
</tr>
<tr>
<td>Median</td>
<td>2h 40min</td>
<td>2h 20min</td>
</tr>
<tr>
<td>Minimum</td>
<td>10min</td>
<td>10min</td>
</tr>
<tr>
<td>Maximum</td>
<td>18h 20min</td>
<td>74h</td>
</tr>
<tr>
<td>5th percentile</td>
<td>20min</td>
<td>10min</td>
</tr>
<tr>
<td>95th percentile</td>
<td>5h 57min</td>
<td>10h 20min</td>
</tr>
</tbody>
</table>

The average duration is significantly higher than for residential participants – about 3 hours compared to 2 hours for residential participants. This could be at least partly explained by the fact that commercial vehicles are generally used only for a part of the day, and are therefore more likely to remain plugged in for longer (e.g. during out of office or business hours). The maximum recorded charging events are very long (more than 18 hours for 1-phase meters and 74 hours for 3-phase), and are unlikely to be associated with charging the battery of a single vehicle. Fully understanding the background behind these outlier events is beyond the scope of the available charging data.

The results again suggest that most pool and company vehicles seem to be flexible enough in terms of timing their charging to allow shifting of load from system peak periods to off-peak hours. Delivery fleets appear to have much less flexibility in terms of timing their demand, as they spend most working hours on the road, and then charge for relatively long periods.

3.3. Charging at public stations

The analysis of charging events recorded at public charging points (CPs) is based on the Source London data collected between 1 October 2012 and 6 February 2014. As described in Section 2.2, the data included 491 charging stations operated by four CNOs. A total of 1,656 EVs used the public charging infrastructure over 22,350 recorded events. The total energy delivered through the 491 CPs amounted to 82 MWh.\(^\text{10}\)

Not all CPs were operational during the whole trial period. Given that no information was available on the date of commissioning of individual CPs, it was assumed that CPs were active between the dates when their first and last recorded charging events occurred. Based on that assumption, the evolution of active CPs over the trial period is depicted in Figure 29.

\(^{10}\) For comparison, the most recent quarterly report on the usage of Source London network published by TfL (covering the period 1 January to 31 March 2014) says that the number of charging events recorded was 11,640, while the total energy delivered was 76 MWh. Given that the data available for this analysis covered about 35% of the 1,408 CPs participating in the Source London network, the number of charging events included in the analysis here and the associated energy seem consistent with the total Source London data.
Although 491 CPs are listed in the charging events database, the number of simultaneously active CPs never exceeded 250. The number of active CPs gradually increased over the trial period, peaking between mid-August and end of September 2013, and then decreasing towards the beginning of 2014. For reference, the agreement to monitor the public charging point data agreed between TfL and LCL project covered the period January 2013 – January 2014. Some data was stored into the database even before this period, and some monitoring activities also continued beyond January 2014.

3.3.1. Energy and duration associated with charging events

The cumulative distribution of energy and time associated with individual charging events at public CPs is shown in Figure 30. As mentioned earlier, the events database contained a large proportion of records with zero or very low energy, very high energy, as well as negative or very long charging durations. These events have been discarded from the analysis. The cumulative distributions for the reduced dataset are also depicted in Figure 30.

The cumulative distributions for the reduced dataset were further disaggregated across the four CNOs. The resulting cumulative distributions for energy per charging event are shown in Figure 31, while those for the event duration are given in Figure 32. The figures also indicate the values for the median energy i.e. duration, as well as 5th and 95th percentiles.
The key statistical parameters for the energy and charging duration across CNOs, as well as for the entire dataset, are given in Table 6.
Table 6. Key statistics for energy and duration of charging events at public CPs

<table>
<thead>
<tr>
<th></th>
<th>Average</th>
<th>Median</th>
<th>5&lt;sup&gt;th&lt;/sup&gt; percentile</th>
<th>95&lt;sup&gt;th&lt;/sup&gt; percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Energy (kWh)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>All CNOs</strong></td>
<td>4.59</td>
<td>3.31</td>
<td>0.60</td>
<td>12.72</td>
</tr>
<tr>
<td>ChargeMaster</td>
<td>6.32</td>
<td>5.22</td>
<td>1.31</td>
<td>14.74</td>
</tr>
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<td>PodPoint</td>
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<td>3.37</td>
<td>0.37</td>
<td>13.68</td>
</tr>
<tr>
<td>Elektromotive</td>
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<td>3.11</td>
<td>0.61</td>
<td>10.15</td>
</tr>
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<td>CPMS</td>
<td>7.21</td>
<td>4.70</td>
<td>0.76</td>
<td>19.03</td>
</tr>
<tr>
<td><strong>Duration (h)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>All CNOs</strong></td>
<td>3.16</td>
<td>2.10</td>
<td>0.37</td>
<td>10.53</td>
</tr>
<tr>
<td>ChargeMaster</td>
<td>5.03</td>
<td>3.49</td>
<td>0.59</td>
<td>14.59</td>
</tr>
<tr>
<td>PodPoint</td>
<td>3.87</td>
<td>2.60</td>
<td>0.31</td>
<td>12.94</td>
</tr>
<tr>
<td>Elektromotive</td>
<td>2.62</td>
<td>1.91</td>
<td>0.37</td>
<td>7.69</td>
</tr>
<tr>
<td>CPMS</td>
<td>4.84</td>
<td>4.08</td>
<td>0.25</td>
<td>10.56</td>
</tr>
<tr>
<td><strong>Number of charging events</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>All CNOs</strong></td>
<td>16,309</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ChargeMaster</td>
<td>1,524</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PodPoint</td>
<td>3,207</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elektromotive</td>
<td>11,077</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CPMS</td>
<td>501</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Finally, the frequency distributions of energy and charging durations for the entire dataset and for individual CNOs are depicted in Figure 33 and Figure 34.
Figure 33. Frequency distributions of energy for charging for different CNOs
3.3.2. Total energy and number of events per charging point

This section evaluates the intensity of usage of individual CPs over the trial period. A number of factors are expected to affect the volume of energy delivered through a given CP, such as its installation date, location, and plug type and rating. In order to make this assessment, the cumulative distributions of total energy delivered per CP and total number of charging events recorded per CP are given in Figure 35 and Figure 36, disaggregated across different CNOs.
The rate of usage illustrated in the figures above suggests that most CPs are used rather infrequently. Only about 10% of CPs are used more than 100 times over the 16-month period, with CPs associated with certain CNOs (e.g. Elektromotive, with one of their CPs catering for 1,100 events) being used more intensively than those operated by others (e.g. ChargeMaster). It has to be noted that the total number of charge events is also related to how long a CP has been assumed to operate, and this period varies considerably across different CPs.

In order to consider the length of time a given CP is in operation, Figure 37 quantifies the average daily number of charge events per CP taking into account the length of period during which a CP was active (which is assumed to be defined by its first and last recorded charging events). There is a significant number of CPs for which only one charging event is recorded and they are hence assumed to be active for that one day only. The figure suggests that about 17% of CPs are used at least once per day, however this number would most likely be lower had the information been available on the actual lengths of time during which CPs were active.
Figure 37. Distribution of average daily number of charging events per CP

The data suggest that with the EV uptake being at a very early stage, many CPs have not yet achieved daily usage and there is significant under-occupancy at banks of CPs.

3.3.3. Usage of public charging points from the EV perspective

Using the unique vehicle ID information available from the dataset it is possible to evaluate how often different EV users used public CPs and how much energy they charged when visiting CPs. Figure 38 therefore quantifies the cumulative distribution of the number of charging events at public CPs recorded per single EV, to the extent the data was available. Although some vehicles used public CPs very often (the maximum recorded number of visits for a single EV was 675), most of them only used public CPs occasionally. The average number of visits per individual EV was 11.8, but that figure is heavily dominated by high-usage vehicles. The median number of visits was only 3 during the trial period.

Figure 38. Cumulative distribution of total number of charging events per single EV

A great majority of EV users (82%) resort to a public CP less than once a month. This suggests that early adopters appear to be using the public charging infrastructure more as an insurance policy at this time.

Similarly, Figure 39 quantifies the cumulative distribution of total energy delivered to a single EV through public CPs over the trial period. The average value is 54.4 kWh, while the median is 12.8 kWh (equivalent to the distance of about 65 km).
Another parameter of interest is how many different CPs a single EV visited over the trial period. This is illustrated in Figure 40. It can be observed that about 80% of vehicles visited up to 3 different public CPs over the trial period, while only 5% visited 7 or more CPs.

3.3.4. Implied power associated with charging events

From the data available for the charging events at public CPs it was possible to find the implicit charging power by dividing the energy delivered per event with the duration of the event. In the absence of more detailed data on the power ratings of individual CPs or charging profiles associated with individual events, the assumption was made that charging occurs at constant power equal to the implied power i.e. the ratio between energy and duration of each event.\footnote{In addition to the ratings of public CPs operated by different CNOs, the maximum attainable charging power for a given event also depended on the EV on-board charger (e.g. a Peugeot iOn will charge at 16 A even when connected to a CP rated at 32 A).}
The values thus obtained varied significantly, as illustrated in Figure 41 where pairs of values for energy and duration of each event are plotted. To improve visibility, the figure does not display very high durations and very high consumption values. The correlation coefficient for the scatter plot in the figure is 0.53 and it appears that the data still contain a considerable amount of unreliable information. Nevertheless, clusters of measurements 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 implied powers of more than 3.7 kW, which is in line with the small number of CPs allowing fast or rapid charging in the Source London network.

Clearly, the various combinations of vehicle, charge post, and state of charge when charging commences do not result in the full rated capacity of the CPs being drawn on every occasion. This is a significant learning point, which brings into question the value in designing network connections of banks of CPs for full rated capacity and full occupancy.

This also means that EV drivers may not yet have developed a perceived ‘standard of service’ from a charge post, since the experience from one to the next is quite variable. Coupled with the fact that charging events last several hours, this reinforces the trials which Low Carbon London did to turn-down charge posts on a round-robin basis, and at a level and duration that did not significantly impact the customer’s experience of charging. In the long term, once the charging posts become utilised more intensively, they could also provide a source of Demand Side Response (DSR).

Cumulative and frequency distributions of implied charging power levels are depicted in Figure 42. About 98% of observations are at or below 3.7 kW, i.e. the power rating of standard charging stations.
3.3.5. Generating charging profiles for public stations

Assuming that all charging events require a constant power profile at the level of implied power, charging profiles have been constructed for all CPs in 10-minute resolution, i.e. in a similar format to the metered charging data. In order to ensure sufficient diversity, only those days were included in the calculation where the number of active CPs was at least 100.

Average and maximum charging profiles have been constructed using the same approach as for residential and commercial EV charging in Sections 3.1 and 3.2, and are depicted in Figure 43. The two profiles are plotted against different axes due to the difference in their orders of magnitude. The average charging profile per CP peaks around noon at around 0.1 kW. Average daily energy requirement per CP is 1.18 kWh. The average charging diagram also clearly reflects the fact that very little usage occurs during night time. The maximum power diagram appears to be rather spiky. The peak recorded power was about 1.7 kW, but only occurred in a single 10-minute interval and could be considered as an outlier. No other interval exceeds 1 kW by any significant amount.

Finally, the average charging profile per CP is differentiated according to different days of the week, as presented in Figure 44. It is immediately obvious that the energy consumption during working days is higher than over the weekend. The average daily energy requirement during the week is 1.31 kWh, while those observed for Saturday and Sunday are 0.97 kWh.
and 0.73 kWh per day, respectively. It is also possible to notice that the CP demand picks up more slowly during the weekends, and peaks around 2pm.

![Graph showing average charging power per CP for different days of the week]

**Figure 44. Average charging power per CP for different days of the week**

It is considered less appropriate to explore the diversity of CP load, since the CNO business model is to eventually achieve high levels of utilisation at individual CPs and high levels of occupancy at banks of charge posts in order to recoup the fixed investment and maintenance cost as soon as possible. For the same reason it is not envisaged that a significant potential would exist for providing system services by public CPs through controllable charging. The scope for smart charging opportunities is therefore expected to be significantly narrower than for home charging points.
4. EV logger data analysis

The data collection in the LCL EV trials also included a significant amount of information collected from the on-board data loggers. The data included a great amount of detail on the driving behaviour: journey start and end times, average and maximum speed, battery state of charge (SoC) before and after each driving and charging event etc. The EV sample participating in the data logging activity included 22 residential and 8 commercial vehicles. The subset of 10 of the 22 residential EVs with data loggers also had their charging monitored.

The data on driving, parking and charging patterns is also highly valuable to establish the potential flexibility of EV charging, so that the required energy for battery charging is potentially delivered at times that are more beneficial for the electricity system and are at the same time available for charging given the vehicle’s driving patterns.

As discussed in Section 2.3, a number of events appear to have gone unrecorded by data loggers. This is for instance reflected in very long parking or driving events that last for several months, although the events nominally cover the entire (or almost entire) duration of the trial period. The primary reason for this was the interference between the loggers and batteries, which required disconnecting the loggers for certain periods of time.

A number of other inconsistencies have been further identified in the logger data, such as: duplicate events; SoC decrease after charging or increase after parking or driving; events with negative energy being transferred etc. Some of these inconsistencies could be attributed to the fact that the logger data are GPS-derived and hence exposed to issues such as temporary timing errors or reduced quality of satellite coverage.

When comparing the vehicle logger data against the information in the charging database for the 10 vehicles with both sets of data, it was observed that the energy captured in charging events recorded by EV loggers is several times lower than the one found through the metered charging data.

4.1. Specific consumption and average distances

The data on distance travelled and the charging energy required allow for calculating the specific consumption of electricity by EVs per kilometre of distance. This value should not be affected by any missing trip data as they would be omitted both from the total distance as well as from the total energy.

When this ratio is computed for the 22 residential vehicles, the average net energy consumption per kilometre is 0.145 kWh/km. This net energy is the energy transferred by the battery to the vehicle drive train; the energy taken from the grid needs to be adjusted for charging losses. Assuming the typical losses of around 15%, the gross specific electricity consumption amounts to 0.17 kWh/km. The specific net consumption for the commercial fleet is found to be higher, 0.188 kWh/day.

The average distances for the residential and commercial participants resulting from the logger data were found to be 9 km and 5.7 km, respectively. These values are lower than
what one would expect to find in an average fleet. The missing data discussed earlier could provide a possible explanation for that.

4.2. Distribution of distances for individual trips

The data loggers recorded among other information the distances associated with individual journeys. In order to provide an insight into the typical distances travelled in a single trip in an urban environment such as the one used as a background for LCL EV trials, the frequency distribution of trips over distances travelled is depicted in Figure 45 for both residential and commercial EV samples.

Both charts are based on driving events recorded by data loggers. There were in total 10,857 trips recorded in the residential sample, and 2,597 trips in the commercial sample. Out of those, however, 2,035 and 590 events had a distance of 100 meters or less, for residential and commercial samples respectively. These short trips, often resulting from the data loggers recording very small vehicle movements combined with very short parking events, have been ignored when constructing Figure 45. Further statistical parameters associated with distances per trip are provided in Table 7.

![Figure 45. Distribution of distances of individual trips in residential (left) and commercial sample (right)](image)

| Table 7. Statistics of distances per single trip for residential and commercial EVs (in km) |
|-----------------------------------------------|-----------------|-----------------|
| Average | 6.67 | 6.36 |
| Median | 3.55 | 3.54 |
| Minimum | 0.11 | 0.11 |
| Maximum | 151.92 | 183.68 |
| 5<sup>th</sup> percentile | 0.58 | 0.41 |
| 95<sup>th</sup> percentile | 24.72 | 20.00 |

There is no significant difference in terms of average and median distances per trip between the residential and commercial participants. A great majority of trips falls below 10 km, which rather common for an urban environment. About 95% of trips were below 25 km for residential and below 20 km for commercial users.

4.3. Charging at home and in other locations

Despite the identified gaps in energy requirement and most probably total distances travelled, it is interesting to analyse the frequency of charging for individual vehicles according to the location. Given that home addresses for residential participants were
generally not available (and similarly for the business addresses for commercial vehicles), it was necessary to infer those locations from the charging data. In a rather straightforward manner, it was assumed that each participant’s “base” location is the location where the participant chose to charge most frequently. This enabled the quantification of the number of charging events that occurred at home (i.e. at the locations of organisations involved in the commercial trial) versus those that occurred elsewhere. This is quantified in Figure 46, where the charging events for each vehicle in residential and commercial samples are grouped into first-choice location, second-choice location and other charging locations.

The figure suggests that a great majority of users decided to charge their vehicles at home or at their office. This was the choice made for 84% of residential and 87% of commercial charging events. About 6% of charging events in both groups could be attributed to second-choice locations, which could be conveniently located charging points near large retail outlets or at service stations. The rest of charging events took place at various other locations.

Despite predominantly relying on home/office charging points, some users were much more prone to using alternative charging facilities. For instance, users number 12 and 13 in the residential sample used their home locations in only about 40% of charging events, using public charging infrastructure to meet the remaining charging requirements.\(^\text{12}\)

4.4. Use of fast charging points

The EV logger data specified among other parameters the energy transferred during charging event and the event duration. If the ratio between those two parameters is found for each charging event, it is possible to estimate the charging power for different events. It was further assumed that those events with implied charging power of 7 kW or more could

\(^{12}\) It is worth mentioning that the Source London membership offered free charging at public CPs for the duration of these trials. Current membership model for Source London only requires an annual payment of £10 which allows the user to use any of the CPs in the network for an unlimited number of times with no additional fees.
be considered as fast charging. The total number of events disaggregated into slow and fast charging has been determined for both residential and commercial samples and is presented in Figure 47.

![Figure 47. Number of charging events per vehicle in residential and commercial samples](image)

The figure shows that a great majority of energy is supplied from standard charging points, with only a small percentage of charging events occurring at (public) fast charging stations. The number of fast charging events for the residential sample is around 4% the total number of events, while for the commercial fleet this is only about 1.7%.

### 4.5. Distribution of SoC before and after charging
EV users generally plug in their vehicles to be charged at various levels of battery SoC, depending on the number of factors such as typical distances travelled, user’s attitude towards range anxiety, and the availability of alternative charging points outside the users’ homes or offices.

Data loggers deployed in the LCL EV trials allowed for identifying the statistical characteristics of the decisions when to start or stop charging with respect to the level of energy in the battery. In the first step, the scatter plots of start versus end SoC are presented in Figure 48. For easier reference, the identity lines are also indicated.

![Figure 48. Scatter plot of start vs. end SoC for residential (left) and commercial (right) EV samples](image)

The plots indicate that although various combinations of start and end SoC values are observed, the most common end SoC values are around 90% and 98% for residential and commercial samples.
89% for commercial users. These levels can be interpreted as the batteries being charged to the full, with the battery management system slowing down the charging as the SoC approaches 100%. Another likely contributing factor is the possible degradation of battery capacity at lower ambient temperatures, as well as the impact of battery ageing, reducing the ability to reach 100%.

Frequency distributions of start and end SoC for both samples are further presented in Figure 49. In addition to frequency histograms, the charts also represent the average start SoC values for individual vehicles in the sample as red crosses, and end SoC as green crosses at the top of the charts. A single pair of a red and green cross at the same height corresponds to the same vehicle in the sample. These pairs are sorted from bottom to top in the order of increasing mean start SoC.

Figure 49. Frequency distributions of start and end SoC for residential (top) and commercial (bottom) EV samples

The average values for start and end SoC indicated in the figure suggest there is a certain correlation between the two parameters, i.e. that the users who start charging at a lower SoC are also more likely to stop charging at a lower SoC and vice versa. The figure also confirms that while a great majority of charging events are terminated when the SoC reaches about 90 to 100%, the start SoC is much more uniformly spread across the range of observed start SoC values.
What this analysis also suggests is that most users, charging their batteries to the full, have sufficient time available to leave their EV plugged in for long enough to reach an almost 100% SoC. This again confirms previous judgements about the existence of a significant flexibility in terms of timing the charging events towards more favourable periods in the day from the grid perspective, while still delivering the required amount of energy to the users without affecting their capabilities to undertake the intended journeys.

4.6. Opportunities for smart EV charging to support network management
In this section the driving and charging data collected via data loggers is 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 and presented here for this purpose, and several case studies are conducted with the fleets of 10 and 22 residential vehicles included in the data logging activity (the subsample of 10 EVs corresponds to those vehicles that both had journey loggers and their charging monitored).

4.6.1. Input data and assumptions
The key input into the model is the information on charging, driving and parking events, which was taken for a selected day in March 2014 that had an adequate coverage of EV events. The key parameters of EV charging demand and driving behaviour for that day are summarised in Table 8. As indicated in the table, not all vehicles are charged on the selected day, which can be expected in a realistic situation.

<table>
<thead>
<tr>
<th></th>
<th>Fleet of 10</th>
<th>Fleet of 22</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of vehicles charging during the day</td>
<td>5</td>
<td>10</td>
</tr>
<tr>
<td>Average electricity demand (kWh)</td>
<td>6.7</td>
<td>5.1</td>
</tr>
<tr>
<td>Average time spent on the road (hours)</td>
<td>1.23</td>
<td>1.19</td>
</tr>
</tbody>
</table>

The resulting (uncontrolled) charging profiles, obtained using the implied power values based on energy and duration of individual events, are presented in Figure 50. The coincident peak demand for the sample of 10 is 16.3 kW, while for the sample of 22 it is 20.3 kW. Note that although the sample size increases more than twice, the coincident peak only increases by about a quarter, as the result of increased diversity within the sample and of lower average consumption in the larger sample.
Figure 50. Uncontrolled demand of residential EV samples

The opportunity to manipulate EV demand will be investigated both with respect to the EV demand alone as well as for the case where EV demand is superimposed on the example baseline demand of residential consumers. The residential demand profiles used to illustrate the methodology were based on the smart metering data and the analysis carried out in the accompanying LCL report quantifying the demand diversity of households involved in LCL TOU trials [13]. The number of customers in the analysed area was assumed to be equal to the number of vehicles in the sample. The residential demand profiles for 10 and 22 customers used in this analysis are for illustrative purposes only, and are presented in Figure 51.

Figure 51. Baseline demand of residential consumers

4.6.2. Peak demand management model

The objective of the peak demand management model is to optimise smart charging decisions in order to minimise the total peak demand for the EV fleet or the local area (EV fleet plus local consumers). The model does this while respecting the constraints related to when the vehicles are parked and when they are on the road.

The model is allowed to shift EV charging demand only within the stationary periods immediately following charging events i.e. before the following journey begins. In other
words, the model ensures that the same energy is delivered to the battery before the next journey is taken (or before the end of the day, whichever is sooner).

A low level of penalisation is introduced for deviations from the original charging profiles (i.e. for following smart charging strategies) in order to focus the smart charging actions only when they affect the peak demand. The peak minimisation model is implemented as a linear programming model using the FICO Xpress platform [11].

4.6.3. Case study results

10 vehicles without baseline demand

The resulting charging profile with minimised peak of the aggregated demand of 10 vehicles is shown in Figure 52. It can be observed that the coincident EV peak reduced 3.3 times, while still ensuring all energy is delivered when vehicles are stationary. Most smart charging actions shift charging demand from peak hours (around 6-8pm) towards the late evening hours.

![Figure 52. Uncontrolled and optimised charging profile for 10 residential EVs without baseline demand](image)

22 vehicles without baseline demand

The minimised peak of the aggregated demand of 22 vehicles is shown in Figure 53. The coincident EV peak demand reduces about 2.2 times in this case. The smart charging actions are again focused on shifting demand from peak hours towards later in the evening. It is also possible to observe that an intermediate peak occurring at mid-day is also successfully resolved through demand shifting.
10 vehicles with baseline demand

The optimised charging profile minimising the peak of the total demand of both residential consumers and 10 EVs is shown in Figure 54. It is evident that smart charging is in this case capable of reducing the total peak to the level before introducing EVs. The EV consumption during peak hours is effectively reduced to zero, suggesting high flexibility of EV demand with respect to shifting.

22 vehicles with baseline demand

Finally, the optimal charging schedule for the case of 22 EVs embedded into a residential area with 22 customers is presented in Figure 55. The peak demand for this case is reduced by 11.8 kW, however the EV demand in this study could not be reduced to zero during peak hours, as there was one vehicle that was charging between about 7pm and 8.30pm and made a journey immediately afterwards. The resulting increase in peak demand from the baseline profile is exactly equal to the assumed charging power of that vehicle, about 3.8 kW.
Figure 55. Uncontrolled and optimised charging profile for 22 residential EVs with baseline demand

To conclude with, the potential to shift residential EV charging demand without compromising the users’ journey requirements seems significant. It is further re-assuring that the results presented in this chapter replicate, for real users driving real journeys, and based on real charging behaviour, the results simulated in the previous ENA report [8] that were based on assumed charging behaviour.
5. Conclusions and recommendations

5.1. Main findings

5.1.1. Residential vehicles
The residential EV trials have confirmed the assumption made in previous studies that if EV charging is not controlled, the additional demand will result in high peaks which broadly coincide with the time of existing system peak demand, putting the electricity system infrastructure under additional stress. The highest demand for residential EV charging is recorded between 6pm and midnight, with very low demand during night and early morning hours. Residential EV demand during weekends is lower than for workdays, although much less so for Sunday when significant charging occurs presumably in anticipation of the following working week. The average daily demand for charging is about 3.5 kWh, which corresponds to around 17.5 km in distance travelled. This energy is slightly lower than the assumptions made in previous studies by the authors based on a nationally representative sample. This is not unexpected given that urban environments tend to be characterised by shorter driving distances.

According to the vehicle logger data, a predominant share of EV charging demand is met through home charging posts. Only on about 16% of occasions did the residential users top-up at public charging point. They therefore appear to be using the public charging stations as an ‘insurance policy’ at this time outside the main home location. The average observed duration of charging events was about 2 hours, with only a small number of events taking more than 5 hours. The median distance associated with a single journey undertaken by residential EVs was around 3.5 km, while 95% of trips were shorter than 25 km.

There is a very regular diversity effect observed in the residential EV sample; for instance, the diversified peak demand per vehicle for the full sample of 54 EVs is about 25% of the peak demand for individual vehicle. Diversity effect is less pronounced but still visible in smaller samples, as expected, providing an important input into the network planning process i.e. ensuring that the network infrastructure is designed to cope with the total of baseline and EV demand.

Significant variability in charging and driving data is observed both between different vehicles as well as for the usage of the same vehicle across different days. This supports the case for probabilistic assessment of maximum expected charging demand rather than relying on average expected values. The desired reliability level of the network will determine which statistical parameters of EV demand should be used to estimate the reasonably expected “worst-case” scenario relevant for network design.

13 The average daily distance driven by residential trial participants established via user questionnaires is between 15 and 25 km depending on the day of week.
Case studies conducted in this report based on vehicle logger data for residential EVs identified a significant potential for smart EV charging to support peak demand management, without affecting the capability of EV users to make their intended journeys. The case studies analysed indicate that most EV demand occurring during system peak hours can be shifted towards late evening and night hours, while still providing the same volume of energy during the same stationary periods.

5.1.2. Commercial vehicles
Energy requirements for commercial EVs vary significantly depending on the vehicle use. For pool and company cars the observed energy demand was significantly lower than for residential users, although it has to be noted that it is measured on a smaller sample. Average daily electricity requirement for this subgroup was about 1.4 kWh, which is sufficient to cover about 7 km per day using a light vehicle (about 2.5 times less than for residential EVs). Delivery van fleets on the other hand had significantly higher energy consumption, at about 14 kWh.

Most charging events (87%) were observed to take place at the main business location, with the minority of charging undertaken at other (public) charging points. Charging events for commercial EVs lasted on average between 3 and 3.5 hours, with about 5% of events taking more than 6 hours for pool and company vehicles and 30% for delivery vehicles. The median trip length recorded by data loggers (which did not include delivery vans) was around 3.5 km, with 95% of trips shorter than 20 km.

Charging demand profiles of commercial trial participants varied greatly depending on the user type. For pool and company vehicles the peak is observed around 10am, gradually tailing off towards the end of normal working hours (6pm). Unsurprisingly, their weekend demand is very low, only about a quarter of workday demand. In line with lower charging energy requirements, the time spent charging is also lower, only about 30 minutes per day on average. Delivery fleet on the other hand had a very low charging demand during business hours on a workday, with a rapid surge in charging demand from virtually zero to about 2 kW per charging point between 3pm and 6pm. Their Sunday demand was almost zero, but on Saturday there was a gradual decline in demand due to vehicles charging from the previous day.

Despite the low size of the pool and company car subgroup (16 vehicles in total with charging data), there is considerable diversity observed with respect to the peak demand observed – diversified peak per EV was found to be about 30% of individual vehicle peak demand. This is in contrast to delivery vans, whose charging patterns were synchronised to a great extent, resulting in a diversity factor of 86%.

It can be expected that commercial EV charging patterns will be much more heterogeneous than residential, as the journey requirements may vary significantly between different types of commercial users i.e. companies. Certain businesses such as e.g. delivery fleets could potentially have a very local and undiversified charging behaviour due to charging patterns being strongly driven by shift work.
5.1.3. Public charging points
The Source London charging stations appear to be used rather infrequently. Great variety in charging duration and energy between individual events has been observed. The median usage frequency for a charging station was 5.5 times per month, and median number of charging events per EV was 3 over the trial period lasting about 16 months (although there was a small number of vehicles with very high usage).

Users generally relied on public charging stations for only a small fraction of their energy requirements i.e. distances travelled. The median energy per day for an EV was equivalent to only about 0.4 km per day. Also, vehicle users tended to use a relatively small number of different charging stations, so that 80% of EVs visited only 3 or less different stations over the observed period.

Peak electricity demand, when averaged across all charging stations, is about 0.1 kW, with the most intensive usage being recorded between 12am and 4pm. Energy demand during weekends is about 35% lower than on workdays.

It is considered less appropriate to explore the diversity of CP load, since the CNO business model revolves around achieving high levels of utilisation at individual CPs and high levels of occupancy at banks of charge posts. For the same reason the scope for smart charging is expected to be significantly narrower than for e.g. home charging points.

However, these findings do suggest some practical solutions which may reduce connection costs, such as sizing the service cable for the full rating of the bank of chargers; but delaying (and therefore eventually socialising when it is required) any upstream reinforcement of network assets. Another alternative could be for simple turn-down schemes between a CNO’s charge posts – once a bank of charge-posts reaches full occupancy, all posts are instructed to fractionally turn down.

5.2. Recommendations
Trial data analysis has shown that the shape of the additional demand due to EV charging will depend on several critical factors, such as the number of vehicles involved, user type or day of the week. Understanding the expectations regarding the future uptake of EVs in a given distribution network therefore seems critical in order to appropriately plan for the projected demand increase and ensure sufficient infrastructure is deployed in a timely manner. To this end, it will be necessary to improve the short- and long-term forecasting of EV uptake and consequently charging demand in future network planning, both in terms of time and location.

The analysis carried out in this report can provide a basis for assessing the diversity of aggregate EV demand depending on the expected evolution of EV penetration in a given area. This assessment will need to be combined with standard assessment of demand diversity associated with network planning. In contrast to traditional network planning based on critical snapshot studies, network planning in the future will need to consider the specific uncertainties associated with EVs, relying more on probabilistic multi-temporal
assessments. The analysis carried out in this report suggests that a diversity factor of about 25% can be used for residential EV user populations of 50 or more,

The analysis based on evidence gathered in the LCL EV trials has demonstrated a massive potential for adopting smart charging approaches in order to support an efficient integration of EVs into electricity systems. Potential benefits from smart charging schemes indicate that their implementation will be vital to efficiently accommodate a high number of EVs in distribution grids.

Data collected in the EV trials have confirmed and verified the previously used EV demand models based on Department for Transport’s nationally representative driving statistics for conventional vehicles. These models will therefore continue to be used in the later stages of the LCL project, after calibration based on the LCL EV trial data, to investigate the opportunities for advanced distribution network planning that involves smart EV charging.

Given the potential to use the flexibility of EV demand to support network management, as illustrated in the case studies in the report, the value of different smart charging control approaches should be thoroughly understood and taken into consideration in distribution network operation and planning, along with the traditional asset-based solutions available to network operators. It should be also taken into account that the EV charging control could be performed not only to support the DNO requirements, but also to provide services to other entities in the system that could have different needs and purposes.

The conclusions of this analysis are expected to remain fairly robust in the next few years. The expectations towards the development of more efficient battery and charger technologies may reduce the total energy requirements but is not expected to have a significant impact on EV demand diversity. As the actual uptake of EVs in the UK gathers pace and there is stronger consumer confidence in the EV technology, it may be advantageous to revisit the findings presented here when the concentrations of EVs in certain local areas begin to approach the numbers involved in this trial.

To that end, expanding the future trial activities to include more vehicles would provide further benefits in terms of boosting confidence in the results of the analysis. Finally, 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 driving distance is likely to make EVs even more attractive given their high capital intensity but relatively low usage cost per kilometre when compared to conventional vehicle technologies.
References


**Project Overview**

Low Carbon London, UK Power Networks’ pioneering learning programme funded by Ofgem’s Low Carbon Networks Fund, has used London as a test bed to develop a smarter electricity network that can manage the demands of a low carbon economy and deliver reliable, sustainable electricity to businesses, residents and communities.

The trials undertaken as part of LCL comprise a set of separate but inter-related activities, approaches and experiments. They have explored how best to deliver and manage a sustainable, cost-effective electricity network as we move towards a low carbon future. The project established a learning laboratory, based at Imperial College London, to analyse the data from the trials which has informed a comprehensive portfolio of learning reports that integrate LCL’s findings.

The structure of these learning reports is shown below:

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