Electric Vehicle Charging Behaviour Study

Final report

for

National Grid ESO

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Element Energy Limited
Suite 1, Bishop Bateman Court
Thompson's Lane
Cambridge
CB5 8AQ

Tel: 01223 852499
Fax: 01223 353475

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Authors

For comments or queries please contact:

Tristan Dodson (tristan.dodson@element-energy.co.uk, 01223 852496)

Shane Slater (shane.slater@element-energy.co.uk, 01223 852492)

Abbreviations

AC	Alternating Current
BEV	Battery Electric Vehicle
DC	Direct Current
DNO	Distribution Network Operator
EV	Electric Vehicle
FES	Future Energy Scenarios
GB	Great Britain
HGV	Heavy Goods Vehicle
km	kilometre
kW	kilowatt
kWh	kilowatt hour
NGESO	National Grid Electricity System Operator
OEM	Original Equipment Manufacturer
OLEV	UK Office for Low Emission Vehicles
PHEV	Plug-in Hybrid Electric Vehicle

Executive Summary

National Grid Electricity System Operator (NGESO) is currently developing its 2019 Future Energy Scenarios (FES), and in response to the increasing uptake of electric vehicles (EVs), aims to represent EV charging behaviour in more detail within FES2019. Previously, EV charging demand profiles have been generated using charging data from small scale EV trials. However, this has limited value because these projects typically include <1,000 early adopter participants, tend to not cover a full year and/or have limited geographic coverage.

This report outlines work carried out by Element Energy, on behalf of NGESO, to develop a set of annual charging demand profiles, covering all 8,760 hours within a year, based upon a dataset of over 8 million real-world charging events collected from major charge point operators.

Data Sources

Charging event data from 2017 and 2018 has been gathered by NGESO from several major providers and operators of charging infrastructure, , and was combined with a large dataset of publicly available charging data released by the UK Office for Low Emission Vehicles (OLEV). These charging events have been categorised into one of four charger types:

- **Residential**: Charge points located at or near EV drivers' homes. These typically have a rated capacity of 3-7 kW.
- **Work**: Charge points installed in workplaces, for use by employees who commute to work using an EV. These typically have a rated capacity of 3-22 kW.
- **Slow/Fast Public**: Publicly accessible charge points, excluding those classified as Work or Residential, with a charging capacity ≤22 kW.
- **Rapid Public**: Publicly accessible charge points with a charging capacity ≥43 kW.

Note 1: Due to the limited number of providers of rapid public charger data the resultant profiles could potentially be back calculated to reveal individual company infrastructure usage; therefore, in this document and the accompanying data set all rapid charger data, descriptions and references have been removed to maintain commercial confidentiality.

Note 2: All data providers (except OLEV) are referred to Source A, Source B etc. to maintain confidentiality

This charger type classification provides an effective trade-off between distinction in usage while ensuring each type has a large enough data volume.

Process to Generate Demand Profiles

Raw data from each data source underwent a cleaning process to remove erroneous charge events, for example, those with very low charge duration or energy that were likely a result of a failed charge event or testing of the charge point. This cleaning process identified and excluded 6.6% of charging events in the raw data. Cleaned charge event data was added to a central database, where events that were duplicated across multiple data sources, such as the OLEV data, could be identified and removed. The resulting database consisted of over 8.3 million charge events. Figure 0-1 illustrates the number of charge events in this database for each charger type for each month in 2017 and 2018.

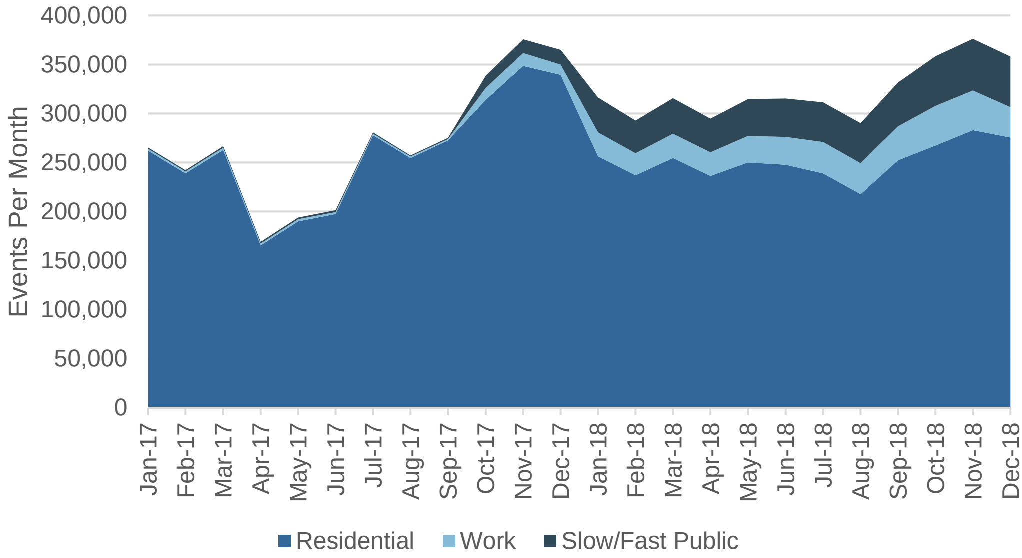


Figure 0-1: Number of charge events per month in collected dataset.

This charge event data then underwent a number of processing steps in order to create a set of full year hourly demand profiles for each charger type. This was necessary to remove the long-term demand trends, driven by increasing numbers of EVs and charge points, such that the final profiles represented a fixed stock of EVs. This enables charging demand from future EV stocks, and different stock growth rates, to be modelled. The processing steps included:

- Correcting for the different numbers of charge points online during the data time series.
- Correcting for the growth in the EV stock which drives increasing demand.
- Identifying the relationship between charging demand and temperature.
- Identifying days of anomalously high and low demand, such as Christmas, Easter and Bank Holidays, to ensure they are reflected in final profiles.
- Combining demand data from multiple years.

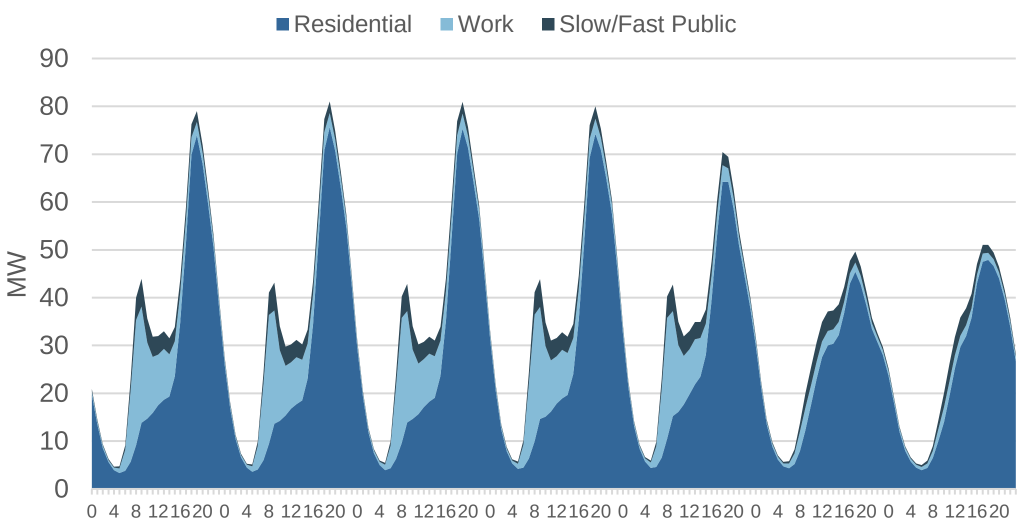
The full profiles generated for each charger type were then scaled by their estimated relative demand and combined to provide a GB-level demand profile, representative of the current stock of EVs. Additional analysis was also carried out to investigate differences in charging behaviour across the 14 distribution network licence areas, as well as the impact of extreme weather events.

Results

Figure 0-2 presents a weekly average demand profile for the GB-level charging demand for 180,000 EVs, which was the EV stock at the end of 2018. This is an average of the final full-year demand profile, and illustrates a number of characteristics of charging behaviour. Note that this is for current charging behaviour, and future charging profiles may show different shapes and distribution of charging demand across the charger types:

- Weekdays (Monday-Friday) display a large peak in the early evening, with a maximum between 7-8pm. This is driven by residential charging, which is currently the largest contributor to overall demand. This evening peak is likely the result of commuters, plugging into charge when they arrive home from work.

- A secondary peak on weekdays is also observed in the morning, with a maximum between 9-10am. This is due to charging at work and slow/fast public charge points, most likely due to commuters plugging in to charge when they arrive at their workplace. This peak is short-lived which suggests that work charge points are typically not used again during the rest of the day, either because employees tend not to vacate the charge point or there are no other EVs on the premises in need of charging. This is despite time spent actually charging typically being between only 1-2 hours.
- On weekdays, there is also a small peak in work charging, which coincides with EV drivers plugging in during their lunch break, perhaps after another employee has vacated the charge point.
- Daily demand (kWh/day) gradually increases from Monday to Thursday, before decreasing back to Monday's level on Fridays. However, peak demand on Friday is noticeably lower than on other weekdays, reduced by 11% compared with Monday to Thursday. These trends are driven by residential charging, and are possibly due to fewer commuters plugging in as they do not need to charge in preparation for a commute the following day.
- Daily demand (kWh/day) on weekends is approximately 25% less than during the week, and the demand profile shows a broader shape. There is no morning peak, and the evening peak is shifted an hour earlier than on weekdays.
- There is considerably less demand from work charging at weekends, with daily demand from this charger type reduced by an average of 73%. This is because fewer people travel into work during the weekend.



	Mon	Tue	Wed	Thu	Fri	Sat	Sun
GWh/day	0.90	0.93	0.94	0.96	0.91	0.71	0.70

Figure 0-2: GB-level weekly average demand profile, averaged over full year for a stock of 180,000 EVs.

Figure 0-3 shows the trend in daily charging demand (kWh/day) at GB level over the course of the year. This shows a clear U-shape, with higher demand in winter and lower demand in summer. January shows a 16% increase in daily demand compared to average, and August shows an 18% reduction. EV energy consumption is known to increase as temperature falls, due to reduced battery efficiency and additional cabin and battery heating load. Winter demand may also be higher if people drive more rather than walk or take public transport. Additional findings include:

- Demand is lowest in August despite July being the warmest month. This is likely to be a result of the school summer holidays, which in England and Wales start in the fourth week of July. A large share of EV drivers will therefore take holiday during this period and will either be out of the country or not using their cars to commute into work or carry out the school run.
- Overall, demand was found to noticeably lower during public holidays. In Figure 0-3, this is clearly visible for the Easter and Christmas to New Year periods, but is also observed on Bank Holiday Mondays where the charging profile resembles that of weekends.
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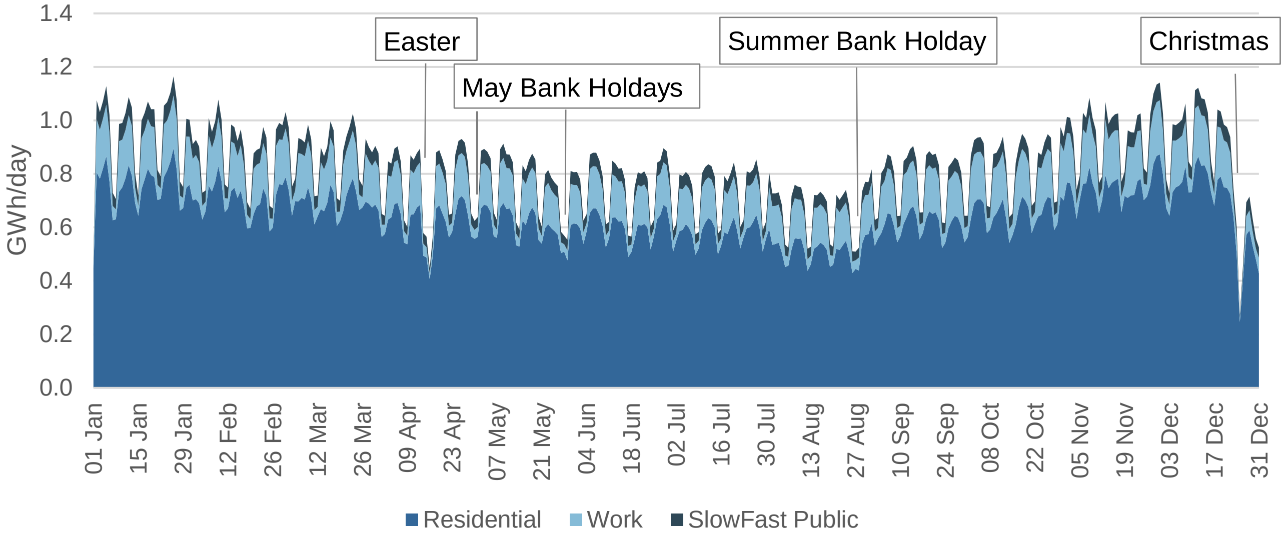

Figure 0-3: GB-level annual daily demand (GWh/day) profile for a stock of 180,000 EVs, based on 2017 temperature profile.

Generating profiles at distribution network licence area level revealed a number of differences across the country. Peak residential and work demand was found to be lower in London compared to all other regions, which is assumed to be due to the lower share of cars used for commuting. The Northern licence area also shows a smaller morning peak at work as well as a secondary peak in the afternoon between 3-4pm. It is proposed that this is due to shift workers plugging in when arriving for day and night shifts.

Over the course of the year, trends in daily demand are generally similar, although residential charging in South and North Scotland show higher demand in July relative to August, while the reverse is true in all other regions (see Figure 0-4). This is likely to be because school summer holidays in Scotland start in the first week of July, rather than the last as in the rest of Great Britain.

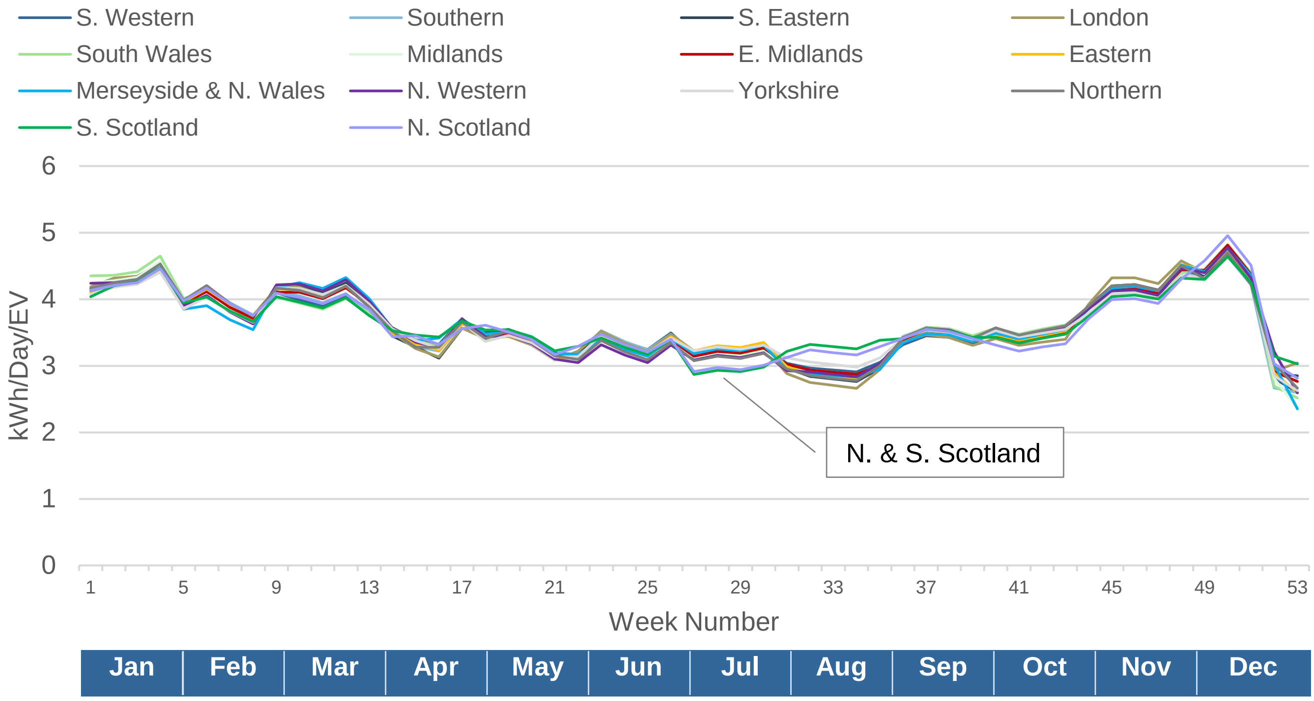

Figure 0-4: Average daily demand for each week over the year, at DNO licence area level for residential charging for an average EV (1,760 kWh/year, receiving 75% demand from residential).

Finally, it was found that charging demand across all charger types was significantly reduced during the so-called 'Beast from the East' storm between the 26th February and 3rd March 2018, which led to widespread traffic disruption due to heavy snow. Figure 0-5 shows the impact on residential charging demand, which saw a gradual reduction throughout the week of the storm. Daily demand on Friday 2nd March at all charger types was approximately 40% lower compared with the preceding and following Fridays, despite the temperature being an average of 4°C lower over the course of the day.

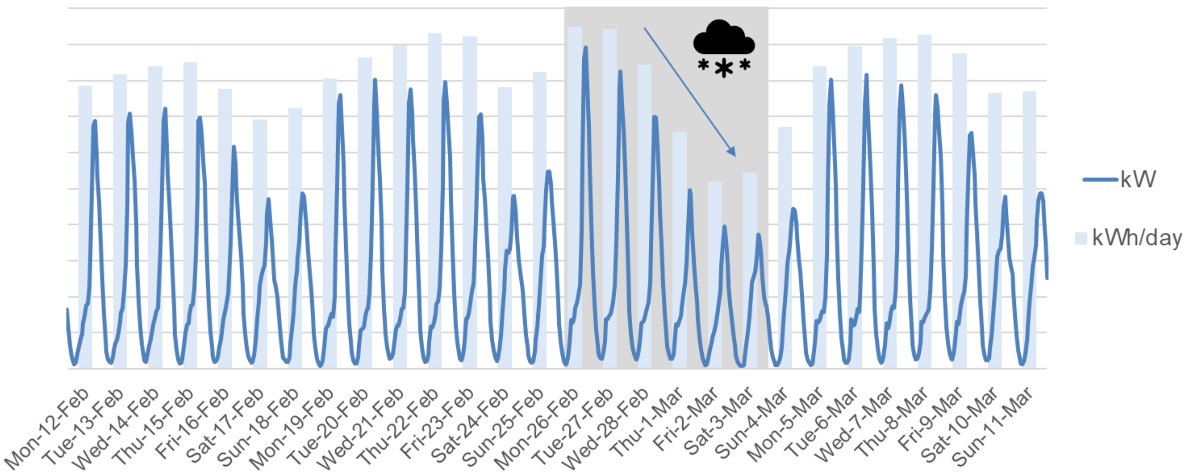

Figure 0-5: Normalized demand profile for residential charging during the 'Beast from the East' storm.

Conclusions

This study has successfully gathered together a database of over 8 million real world charge events and generated a representative full year charging demand profile at hourly resolution. This has enabled NGESO to improve considerably the modelling of EV charging load on the Transmission Network. In the process this work has identified a number of key charging characteristics:

- At GB level, charging demand peaks between 7pm and 8pm on weekdays and is dominated by residential charging demand.
- Work and Slow/Fast Public charging contribute a smaller secondary peak on weekdays in the mid-morning between 9am and 10am.
- Overall demand on weekend days is on average about 25% lower than weekdays and shows a broader demand profile shape that peaks an hour earlier.
- Temperature has significant impact on demand, particularly residential demand where average kWh/day was found to increase by 1.6% for each 1°C fall in temperature.
- During public holidays, demand is reduced, particularly during the Christmas period. The exception to this is rapid charging demand which tends to be higher during the May and August bank holidays and Easter.
- Heavy snow, which causes travel disruption, is found to significantly reduce charging demand across all charger types.

Opportunities for Further Insights

The dataset and findings from this study provide ample opportunity to explore further aspects of charging behaviour. Five areas of interest have been identified:

1. **Exploring further insights:**

This study has made an initial assessment of influencing factors on charging demand (e.g. weekday, temperature, bank holidays). Additional analysis would reveal further factors (both regular and extreme) that could be used to better forecast charging demand.

2. **Stress testing:**

Following on from 1), identifying the major influencing factors would enable “stress testing” of the network in response to extreme weather patterns.

3. **Looking forward to 2030:**

As EV volumes grow over the next decade there is potential for considerable changes in the EV fleet (e.g. EV ranges, BEV/PHEV ratio, higher charging rates, preferred charging location) which will influence the overall charging load.

4. **Exploring flexibility and system benefits:**

The demand profiles in this work are assumed to be unmanaged, but the charging event data can be used to quantify the availability of charging EVs, and thus explore the extent of the flexibility in this demand signal (e.g. to minimise load for DNOs, respond to weather/renewable energy output).

5. Impact of other electric vehicle types:

This study has captured the charging demand of plug-in cars, but as other vehicle segments electrify this will add to demand. This, for example, includes depot-based vans, HGVs and buses that may show different demand profile characteristics.

1 Introduction

National Grid Electricity System Operator (NGESO) is currently developing its 2019 Future Energy Scenarios (FES). Given the increasing uptake of electric vehicles, there is an ambition to model electric vehicle charging behaviour in more detail within FES2019. Previously demand profiles generated from existing charging data have suffered a number of limitations, including:

- They are based upon innovation projects where fewer than 1,000 vehicles or charge points are involved and may not be representative of typical usage.
- They tend not to cover a full year with all charge points or vehicles.
- They are from limited geographical areas within Great Britain (GB), or from outside GB altogether,
- They are assessed for specific network purposes (such as turn down of demand, or smart charging) and so are subject to the Hawthorne effect (whereby trial participant behaviour is influenced by the fact they are taking part in a trial).

This report outlines work carried out by Element Energy, on behalf of NGESO, to develop a set of annual charging demand profiles, covering all 8,760 hours within a year, based upon a dataset of over 8 million real-world charging events. This work has been funded through NGESO's Network Innovation Allowance.

This report is structured as followed:

Section 2 describes the sources of charging event data used in this study.

Section 3 briefly outlines the process through which this charge event data was used to generate full year hourly demand profiles.

Section 4 presents the resulting hourly demand profiles for different charger types, an overall GB-level charging demand profile, demand profiles at distribution network licence area level, as well as analysis of the impact of the 'Beast from the East' storm in February/March 2018.

Section 5 summarises the conclusions from this work, the limitations of this study and suggested future research.

2 Data Sources

As part of this project a large dataset of over 8.3 million charge events, over the period 2017-18, from across GB has been gathered together. This is believed to be the largest single dataset of GB charging data accumulated to date. This data has been provided to NGESO, for the sole use on this project, by several charge point providers and network operators.

Note: All data providers (except OLEV) are referred to Source A, Source B etc. to maintain confidentiality.

In addition, data from these sources has been combined with publicly available charging data provided by the UK Office for Low Emissions Vehicles (OLEV)[1]. Data from each source underwent a cleaning process to remove erroneous charge events, and this is described later in Section 3.1. Charge events were categorised into four *charger types*:

- Residential: Charge points located in EV drivers' homes, and used for overnight charging. This includes on-street charge points installed in lamp posts, such as those operated by Ubitricity, which are intended for use by local residents. These typically have a rated capacity of 3-7 kW.
- Work: Charge points installed in workplaces, for use by employees who commute to work using an EV. This can include some publicly accessible charge points, for example those installed in hospitals and other public buildings, which are used mostly by employees of that premises. These typically have a rated capacity of 3-22 kW.
- Slow/Fast Public: Publicly accessible charge points, excluding those classified as Work or Residential, with a charging capacity ≤22 kW.
- Rapid Public: Publicly accessible charge points with a charging capacity ≥43 kW.

This charger type classification provides an effective trade-off between distinction in usage while ensuring each type has a large enough data volume. A summary of the charge event data provided by each data source (after cleaning) is shown in Figure 2-1 and Appendix 6.1.

Note: Due to the limited number of providers of rapid public charger data the resultant profiles could potentially be back calculated to reveal individual company infrastructure usage; therefore, in this document and the accompanying data set all rapid charger data, descriptions and references have been removed to maintain commercial confidentiality.

[1] https://www.gov.uk/government/collections/energy-and-environment-statistics [Accessed: January 2019]

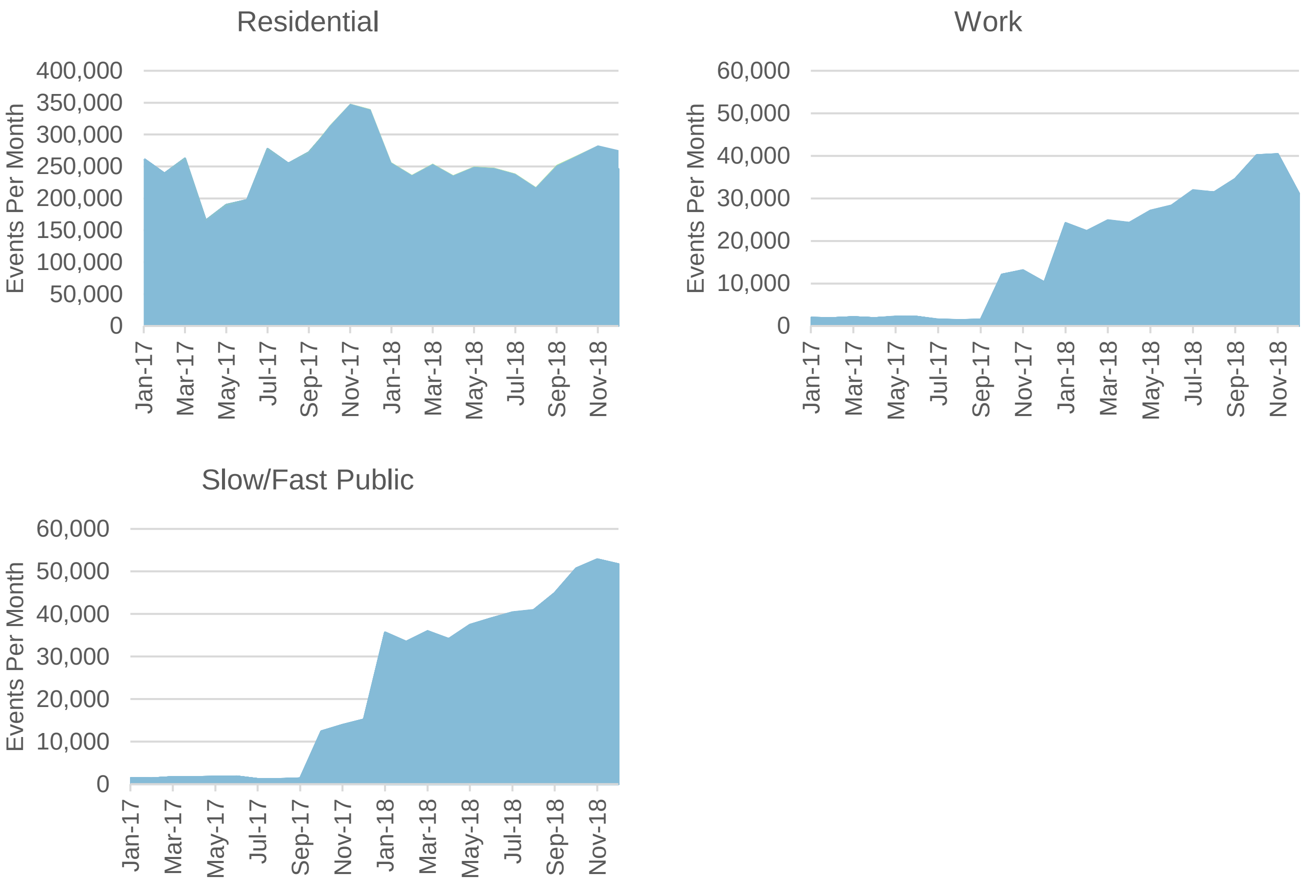

Figure 2-1: Number of charge events per month (after cleaning) for each charger type.

3 Process to Generate Demand Profiles

A flowchart outlining the process through which the raw charging event data is used to generate a GB-level annual charging demand profile, at hourly resolution, is show in Figure 3-1. This involves five steps (1-5) which are outlined in the following sections.

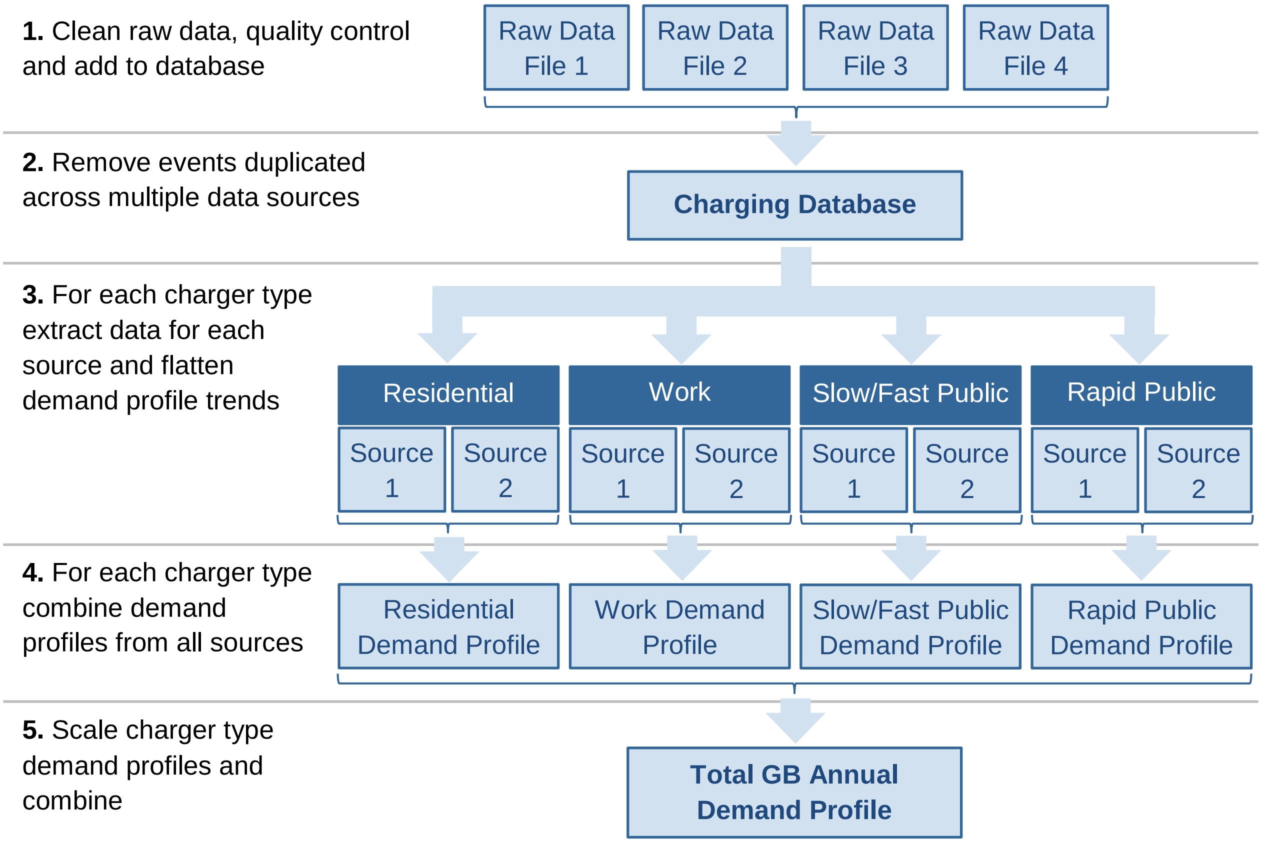

Figure 3-1: Flowchart of data processing method to generate GB-level annual demand profile.

3.1 Data cleaning

To ensure that only successful charge events were used to generate profiles, a cleaning process was implemented on each data source to remove clearly erroneous charge events. These criteria are presented in Appendix 6.2.1, and were defined to remove events with very low and high energy consumption, short plug-in times and charge rates above what the charge point could provide. Duplicate events were also removed. This process resulted in 586,000 (6.6%) of charge events being excluded.

None of the raw charging data sources included both plug-in/out times (when the EV is plugged in and out) and charge start/end times (when the EV actually starts and stops drawing charge). Where charge/end times were unavailable, the charge start time was assumed to be the same as the plug-in time. This approach is likely to exclude the effect of delayed charging functions, where an EV is plugged in but is set to start charging at a later time. This function is used by some EV drivers to delay charging to the start of an off-peak period, such as in an Economy 7 tariff. As a result, the charge demand profiles should be considered as entirely unmanaged (i.e. a worst-case scenario).

The charge end time was estimated by assuming the charge time was the charge event energy (kWh) divided by the rated capacity of the charge point (kW). This approach assumes that EVs charge at the rated capacity for the entire event, which is known to be not the case for rapid charging, where charge rate slows down at high state of charge. This also assumes that the EV is capable of accepting the rated capacity. It is recognised that few models can currently accept more than 7 kW when AC charging, and so charge points with a rated capacity of 22 kW were assumed to charge at 7 kW, unless this resulted in the charge duration being longer than the plug-in duration. In this case the charge duration was set equal to the plug-in duration.

3.2 Adding cleaned data to database and removing duplicates

Cleaned charge event data from each source were added to a central database. This allowed duplicate charge events that were contained in multiple data sources to be identified and removed. Charge events from each charge point provider/operator were distinct, but showed some overlap with data available from OLEV. The OLEV data includes charge events from publicly funded charge points, including the Homecharge and Workplace Charging Schemes, and so some are included in the networks of the charge point providers/operators who supplied data.

OLEV charge events were excluded if other charge events in the database could be identified that fulfilled all of the following criteria:

- Same charger type
- Same local authority or post code district
- Plug-in time within 1 minute
- Energy supplied within 1 kWh
- Plug-in duration within 2 minutes

This results in the exclusion of 15,101 residential, 122 work and 4,645 slow/fast public charge events from the cleaned OLEV data.

3.3 Generating demand profiles and correcting for long term trends

For each data source and charger type, charge events were extracted from the database and converted to a demand profile (kW), with hourly resolution. In general, the resulting demand profiles showed gradual increases in demand as additional charge points came online and the number of EVs increased. Each demand profile was therefore subjected to a number of correction steps to remove these long-term trends. The profiles from each source had to be treated separately as the cause of the trends differed (e.g. the number of charge points grows at different rates and for some sources is not known). The correction steps are as follows (and described in more detail in Appendix 6.3):

1. Demand profile normalized to per charge point to remove influence of increasing demand due to increasing charge point stock. This was only possible for data sources where a unique Charger ID was included, and thus the number of charge points operating on each day could be estimated.
2. Profile corrected for growth in the stock of EVs that use the charge points.
    - For residential and work charge points, each charge point is used by a fixed number of EVs (i.e. 1) so this step is skipped.
3. Influence of temperature, which causes higher charging demand when colder, identified and removed (influence of temperature added back in in Step 5).

4. Profile corrected for any remaining long-term trends by rotating profile such that the average trend line is flat.
5. Once all long-term demand trends have been corrected, influence of temperature is added back into profile.
6. Profile re-scaled relative to its average daily demand (kWh/day). This allows profiles from different sources to be combined later.

An example of a demand profile before and after these correction steps are applied is shown in Figure 3-2.

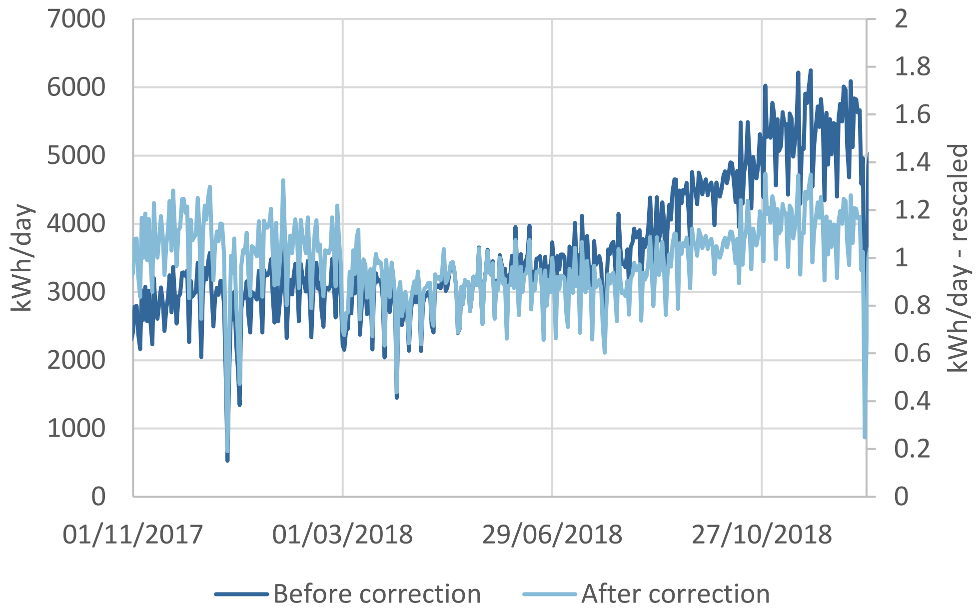

Figure 3-2: Example of demand profile (expressed as kWh/day) before and after correction to remove long-term demand trends.

3.4 Combining demand profiles from each source to create annual demand profiles

For each charger type, the demand profiles from each data source were combined to create a single annual demand profile, at hourly resolution. This employed a number of steps (outlined in more detail in the Appendix 6.4):

1. Daily demand profiles (kWh/day) from each source were combined, weighting by the daily demand in the raw data. This ensures that sources with more charge events contribute more to the final demand profile.
2. The influence of temperature on daily demand was identified and removed. Charging demand and temperature and found to be inversely correlated.
3. The daily demand profile was then rotated to remove any remaining long-term trends.
4. Average daily demand and hourly demand profiles were calculated for each weekday in each month (e.g. March-Monday). These are denoted as *Day Archetypes*.
5. Days of anomalously high and low demand were identified, for example, bank holidays and the Christmas period. These anomalous days were assigned their own *Day Archetypes*.
6. The influence of temperature on daily demand was added back in.

7. The normalized hourly demand profiles of each Day Archetype were scaled by the daily demand, adjusted for the influence of temperature, and stitched together to create a full 8,760 profile. This was then normalized to 1 kWh/year.

3.5 Combining demand profiles from each charger type to generate overall GB-level charging profile

To generate the overall GB-level demand profile, the normalized annual demand profiles from each of the four charger types were scaled by the estimated annual demand for that charger type. For illustrative purposes, the current level of demand has been used, but this process could also be used to model a demand profiles for a future stock of EVs.

Total annual demand per EV was estimated at 1,760 kWh, and the share of charging demand across residential, work, slow/fast public and rapid public charge points assumed to be 75%, 15%, 6% and 5%, respectively. These estimates are based on Element Energy modelling of the current EV usage, and are outlined in more detail in Appendix 6.5. Demand per EV at each charger type was multiplied by the total number of EVs in the GB stock, 180,000[2].

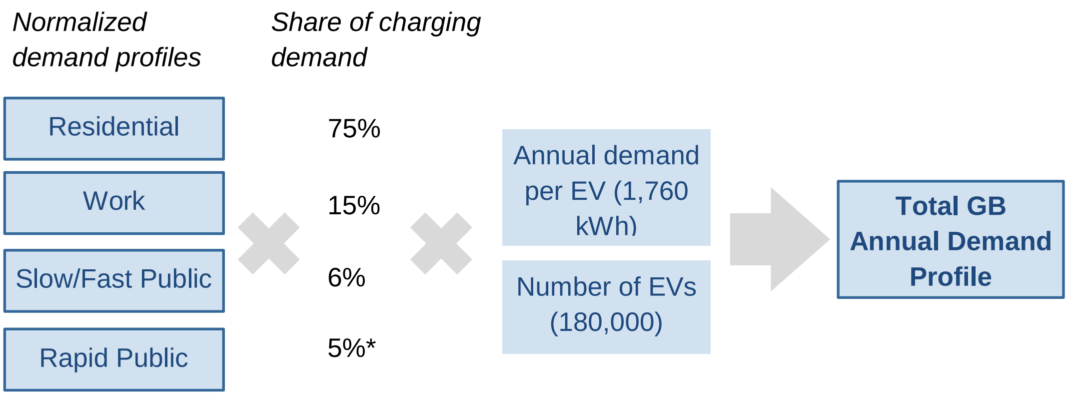

Figure 3-3: Schematic showing how normalized demand profiles from each charger type are combined and scaled to generate overall GB-level annual demand profile. *Shares do not add up to 100% due to rounding errors.

[2] Estimated number of EVs at the end of Q4 2018, based on stock at the end of Q3 2018 (from DfT Vehicle Licensing Statistics Table VEH0130) and sales in Q4 2018 (reported by SMMT, weblink: https://www.smmt.co.uk/category/news/registrations/evs-afvs/)

4 Results

The following sections present the resulting demand profiles generated for residential, work, slow/fast public and rapid public charging, as well as at overall GB level. Due to the number of data points (8,760), the full year hourly profiles are not shown. These are made available in a supplementary spreadsheet. Instead in this report an average weekly demand profile (kW), and a full year daily demand (kWh/day) profile is shown for each charger type.

This section also includes the result of additional profiles generated at distribution network licence area level, as well as the impact on charging demand of the 'Beast from the East' storm in February/March 2018.

4.1 Residential

Figure 4-1 shows the average weekly demand profile shape for residential charging. This has been scaled to represent the weekly consumption of an average EV. Figure 4-2 shows the total daily demand (kWh/day) resulting from this weekly profile.

Between Monday and Thursday there is a gradual increase in daily demand, before a slight decrease on Fridays. Daily demand is then generally lower on weekends. The shape of the residential demand profile shows a large evening peak on weekdays, with a maximum between 7-8pm. This same peak is not visible on weekends which suggests it is largely due to commuters plugging in to charge after returning home from work. The charging behaviour of commuters has already been shown to cause such a peak in previous work[3]. At weekends, the demand profile is spread more broadly throughout the day with a far smaller evening peak, which occurs between 6-7pm.

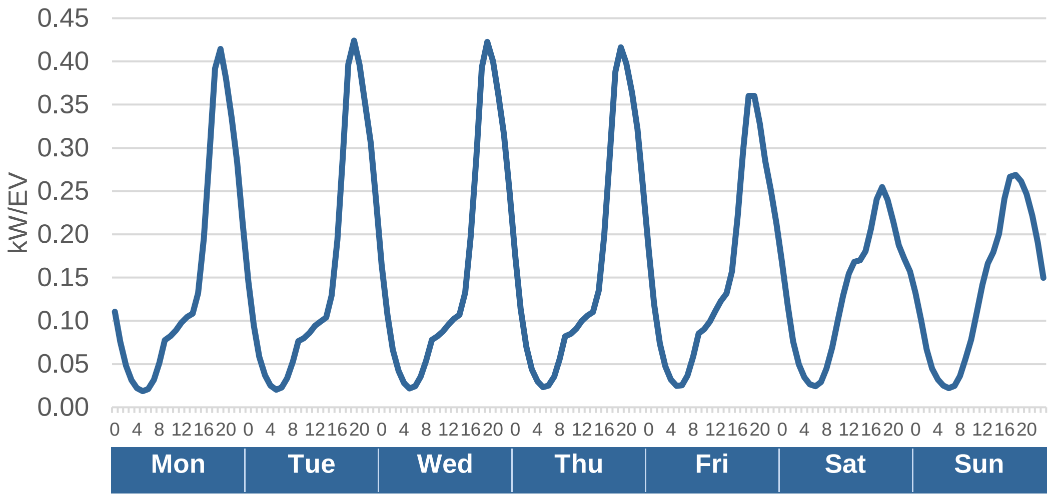

Figure 4-1: Weekly demand profile, averaged over full year, for residential charging for an average EV (1,760 kWh/year, receiving 75% demand from residential).

[3] Element Energy for UK Power Networks (2018) Recharge the Future: Charger Use Study. Available at: http://www.element-energy.co.uk/wordpress/wp-content/uploads/2019/02/20180921_UKPN-Recharge-the-Future_Charger-Use-Study_FINAL.pdf

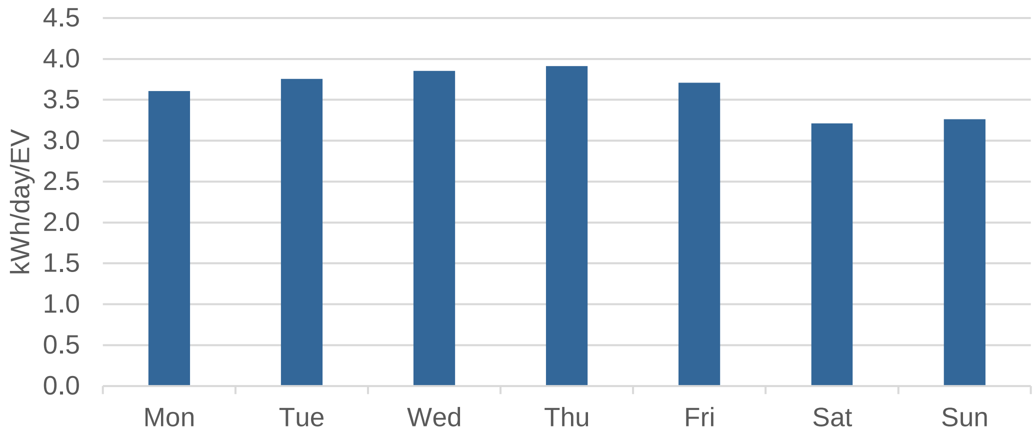

Figure 4-2: Average kWh/day over course of week for residential charging for an average EV (1,760 kWh/year, receiving 75% demand from residential).

Figure 4-3 shows the daily demand profile over the course of the year for residential charging, again scaled to represent demand per EV. A clear trend with temperature can be observed between summer and winter. Demand per day is on average 16% higher in January, and 21% lower in August. On average, daily demand is found to increase by 1.6% for every 1°C decrease in temperature (see Appendix 6.4.2). The reason for this is that battery efficiency is reduced in cold temperatures[4], and there is additional power load from heating the cabin and battery. It is also possible that the frequency of car trips increases in winter as drivers are less willing to walk or take public transport to their destinations.

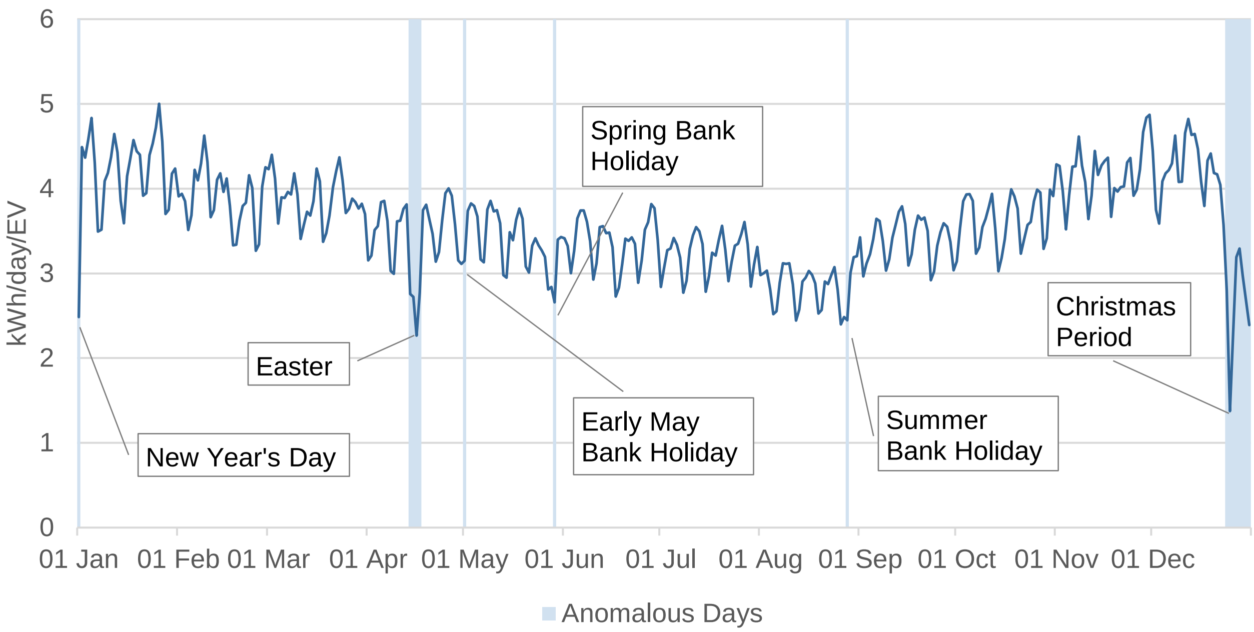

Figure 4-3: Annual daily demand (kWh/day) profile for residential charging, based on 2017 temperature profile, for an average EV (1,760 kWh/year, receiving 75% demand from residential).

[4] Battery University, BU-502: Discharging at High and Low Temperatures: https://batteryuniversity.com/learn/article/discharging_at_high_and_low_temperatures [Accessed: March 2019]

However, despite August showing the lowest average demand, the average temperature is in fact slightly higher in July (16.5°C in July vs 15.6°C in August). This reversal in the demand trend with temperature is likely to be because charging demand is reduced during the school summer holiday, which starts in the last week of July in England and Wales. During this period many EV owners will likely be away on holiday and so will not be using their cars for commuting or the school run.

Days of anomalous demand, which are assigned their own Day Archetype, are also highlighted in Figure 4-3. Demand at residential charge points tends to be significantly lower on bank holidays. This is clearly visible during Christmas, New Year and Easter, when EV drivers might be away or not travelling, but can also be observed on the May and August bank holiday Mondays, when few EV drivers will be commuting to work. Additional detail on anomalous days is presented in Appendix 6.4.5.

4.2 Work

Figure 4-4 shows the average weekly demand profile shape for work charging, which has been scaled to represent the weekly consumption per EV in the stock. Figure 4-5 shows the total daily demand (kWh/day) resulting from this weekly profile.

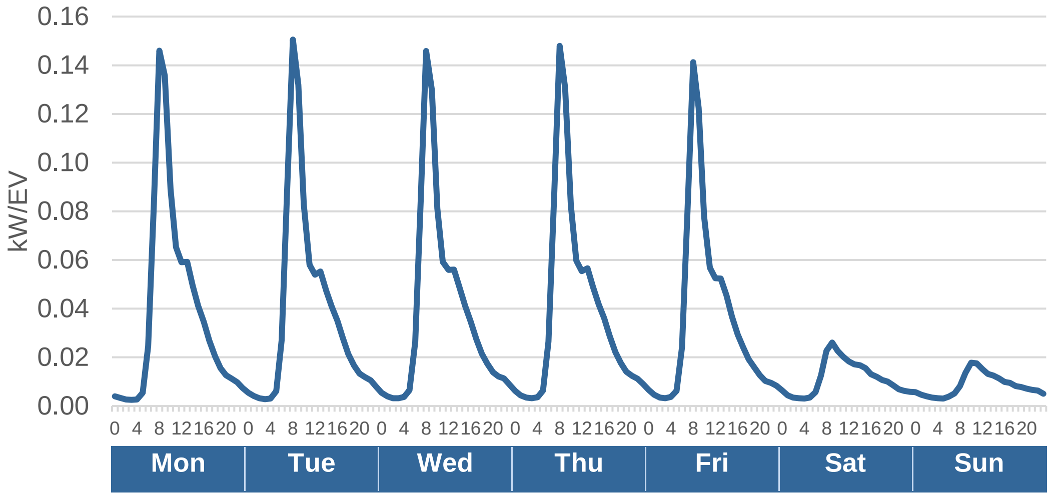

Figure 4-4: Weekly demand profile, averaged over full year, for work charging for an average EV (1,760 kWh/year, receiving 15% demand from work).

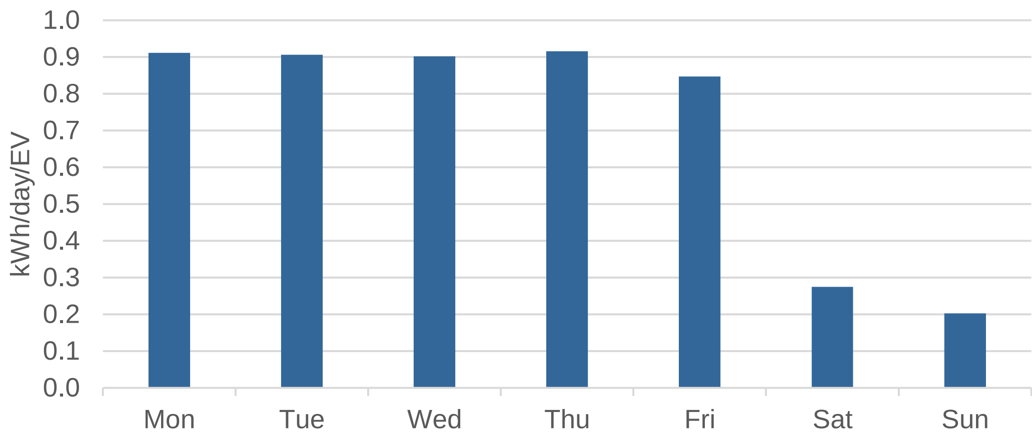

Figure 4-5: Average kWh/day over course of week for work charging for an average EV (1,760 kWh/year, receiving 15% demand from residential).

Charging at work takes place almost exclusively on weekdays, with daily demand on Saturdays 69% lower than an average weekday, and 77% lower on Sundays. This is unsurprising given that workplace charge points are mostly used by commuters, few of whom will travel to work during the weekend. There is also a slight reduction in the daily demand on Fridays compared to Monday-Thursday, presumably because fewer commuters work on this day and the need to charge is lessened if a commute does not need to be made the following day.

The shape of the charging profile shows a strong morning peak on weekdays, with a maximum between 8-9am. This coincides with when commuters arrive at work, suggesting that they tend to immediately plug in to charge. The sharpness of this peak suggests that most EVs need only 1-2 hours to finish charging but remain plugged in for the rest of the day, thereby potentially blocking the charge point for use by other employees. However, there is a small secondary peak between 1-2pm which may be due to some people vacating the charge point and another employee plugging in during the lunch break.

Figure 4-6 shows the daily demand profile for work charging over the course of the year, and similarly for residential charging, there is a clear trend against temperature, with the lowest demand again observed during August. However, the variation is slightly smaller than for residential charging, with 22% higher demand in December and 9% lower demand in August.

The impact of bank holidays is significant, with daily demand at a similarly low level as during the weekend. This is to be expected given that far fewer commuters will travel to work on these days.

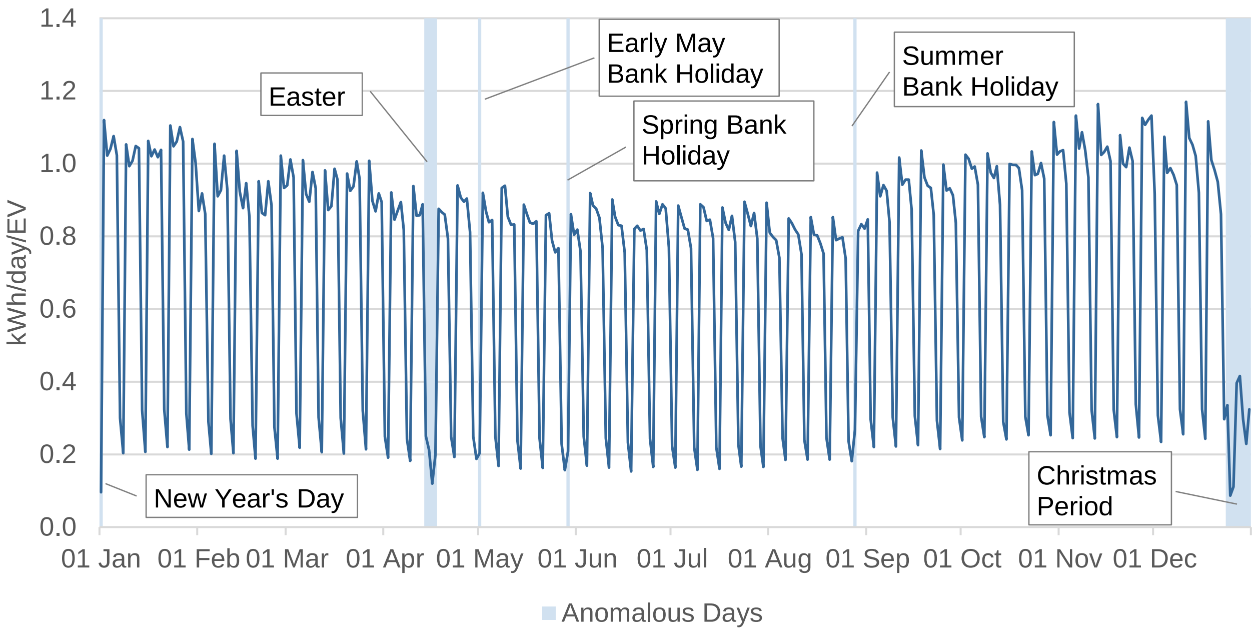

Figure 4-6: Annual daily demand (kWh/day) profile for work charging, based on 2017 temperature profile, for an average EV (1,760 kWh/year, receiving 15% demand from work).

4.3 Slow/Fast Public

Average charging demand per EV across the week at slow/fast public (3-22 kW) is shown in Figure 4-7 and Figure 4-8. Demand remains very similar during Monday to Friday before falling over the weekend, with significantly lower daily demand on Sundays. Note that peak demand per EV is an order of magnitude smaller than for residential charging.

On weekdays, charging demand is found to peak in the morning, showing a similar shape to work charging, however, the peak occurs an hour later between 9-10am. It is likely that some of these charge points are used by commuters, either because they are located at train stations or at publicly accessible locations where commuters work, such as hospitals or educational establishments.

There are also secondary peaks between 1-2pm, which coincides with lunch breaks, and 6-7pm when people may be making their last trip of the day or using a slow/fast public charge point for overnight charging. These peaks are not visible during the weekends, where a considerably rounder profile is observed with a maximum just after midday, further suggesting that the difference in shape is a consequence of commuter behaviour.

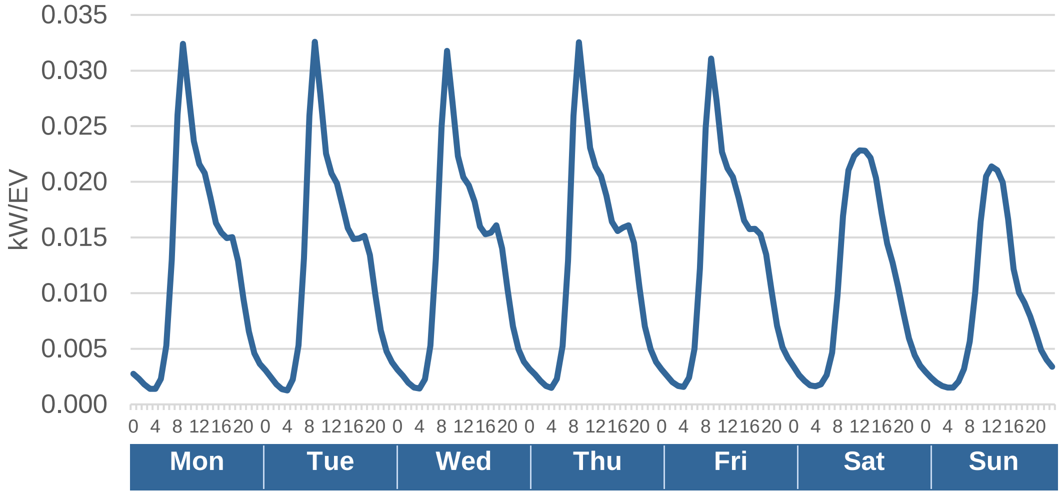

Figure 4-7: Weekly demand profile, averaged over full year, for slow/fast public charging for an average EV (1,760 kWh/year, receiving 5.8% demand from slow/fast public).

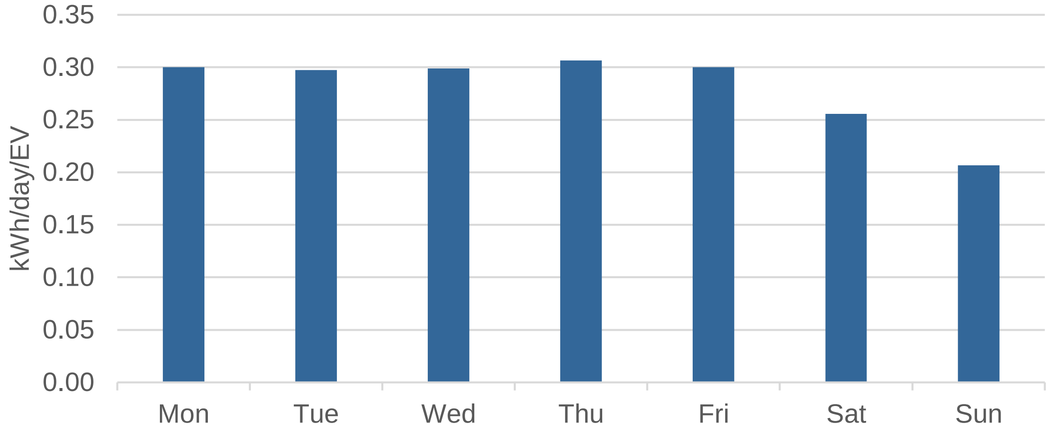

Figure 4-8: Average kWh/day over course of week for slow/fast public charging for an average EV (1,760 kWh/year, receiving 5.8% demand from slow/fast public).

Figure 4-9 shows the trend in daily charging demand over the course of the year, and displays the expected U-shape centred on August. Variation is similar to work charging, with daily demand in January found to be 20% higher than the average, and 12% lower than the average in August. Demand is also reduced considerably during bank holidays. It might be expected that use of slow/fast public charge would be higher on bank holidays as drivers make more trips to shops and leisure sites where charge points might be installed. However, the shape of the charge profile during these anomalous days is similar to weekends, suggesting that the lower demand is due to fewer commuters using these charge points.

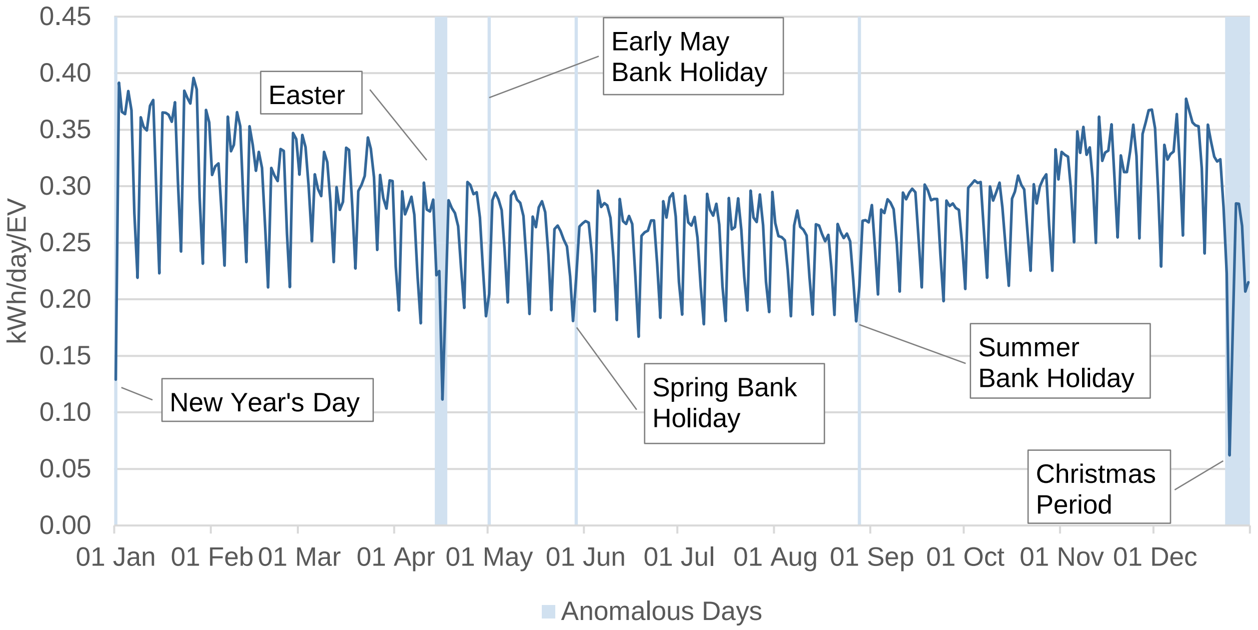

Figure 4-9: Annual daily demand (kWh/day) profile for slow/fast public charging, based on 2017 temperature profile, for an average EV (1,760 kWh/year, receiving 5.8% demand from slow/fast public).

4.4 Total GB-Level Profile

A GB-level demand profile was generated by combining the residential, work and slow/fast public profiles, and scaling by the number of EVs in the stock. At the end of 2018, this was just under 180,000. From the resulting full year demand profile, Figure 4-10 and Figure 4-11 show the average demand profile over the course of a week. Peak EV charging demand is driven by residential charge events during early evening weekdays, with maximum demand occurring between 7-8pm. However, charging at work causes a secondary weekday peak, with a maximum between 9-10am. This is an hour later than the maximum demand from work charging alone, due to the addition of slow/fast public charging demand.

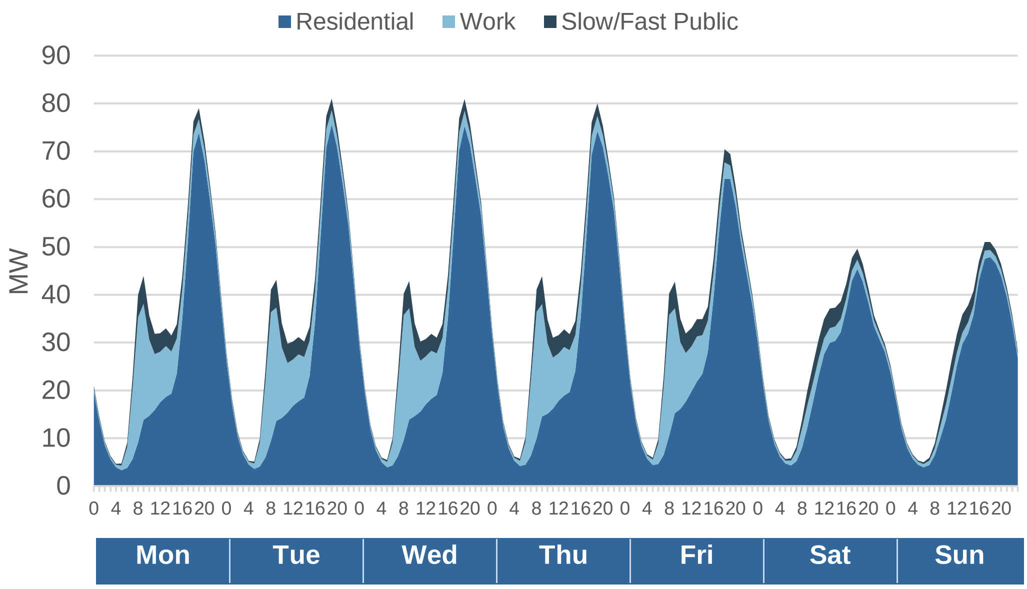

Figure 4-10: GB-level weekly average demand profile, averaged over full year for a stock of 180,000 EVs.

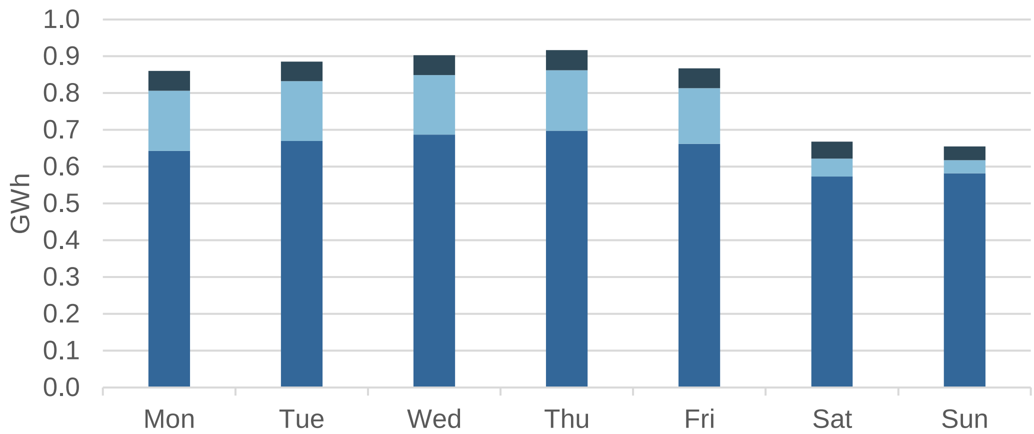

Figure 4-11: Average GB-level daily demand over course of week for a stock of 180,000 EVs.

Total demand per day is found to gradually increase from Monday to Thursday, and then a slight decrease on Friday. Daily demand at the weekend is further reduced by approximately 25% compared to the weekday average, and the peak demand shifted earlier to 5-6pm and reduced by about a third.

Figure 4-12 shows the trend in overall daily charging demand over the course of the year at GB level. As for the constituent charger types, demand is greatest during the colder months, with a 16% increase in daily demand in January compared to the average, and 18% decrease in August.

Reduced demand during the Christmas and Easter periods is clearly visible, as well as on the May and August Bank Holiday Mondays.

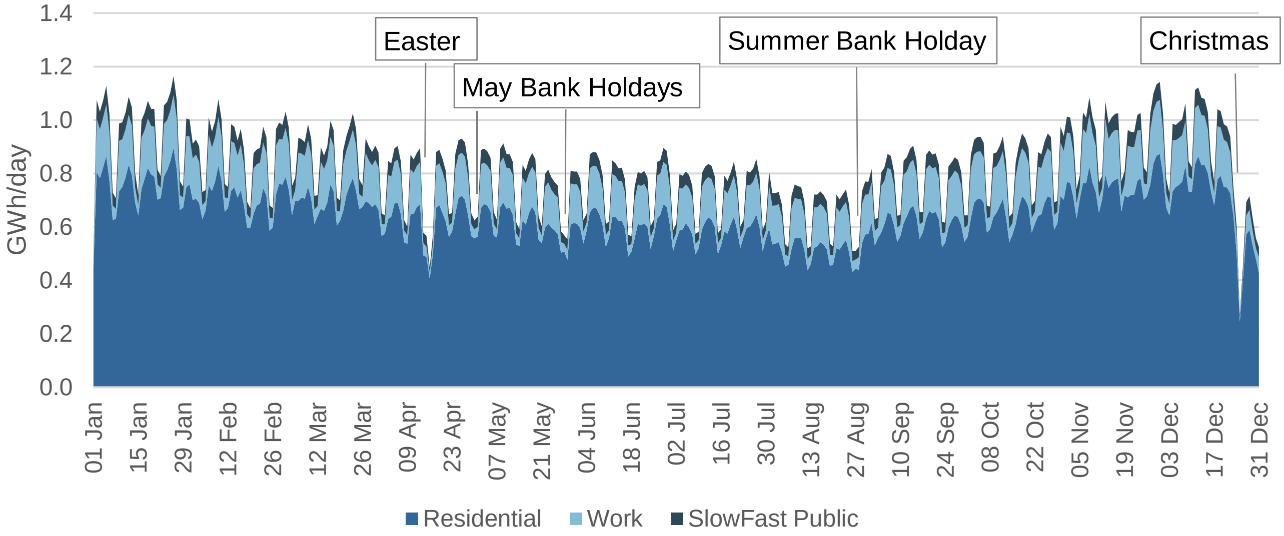

Figure 4-12: GB-level annual daily demand (GWh/day) profile for a stock of 180,000 EVs, based on 2017 temperature profile.

4.5 DNO Licence Area Level Analysis

The full charging event database allows charging profiles to be generated for particular geographies within Great Britain, for example, each of the 14 distribution network license areas. However, the sample size at distribution network licence area level is obviously smaller than GB level, and there is a danger this impacts profile diversity, and therefore fails to represent a large stock of EVs. The following section outlines the effect of charge event data volume and thus diversity on the resulting demand profile.

4.5.1 Profile Diversity Analysis

Figure 4-13 shows the charging demand from all residential charge events in November 2017. On average this sample contains 11,600 events per day and is assumed to be fully diversified. To illustrate the effect of decreasing sample size, this profile is compared with the demand profiles from sub-samples, containing an average of 120 events/day and 60 events/day. At 120 events/day, the resulting profile shows reasonable similarity with the full sample profile, but at 60 events/day the peaks are significantly higher and the profile is no longer diversified.

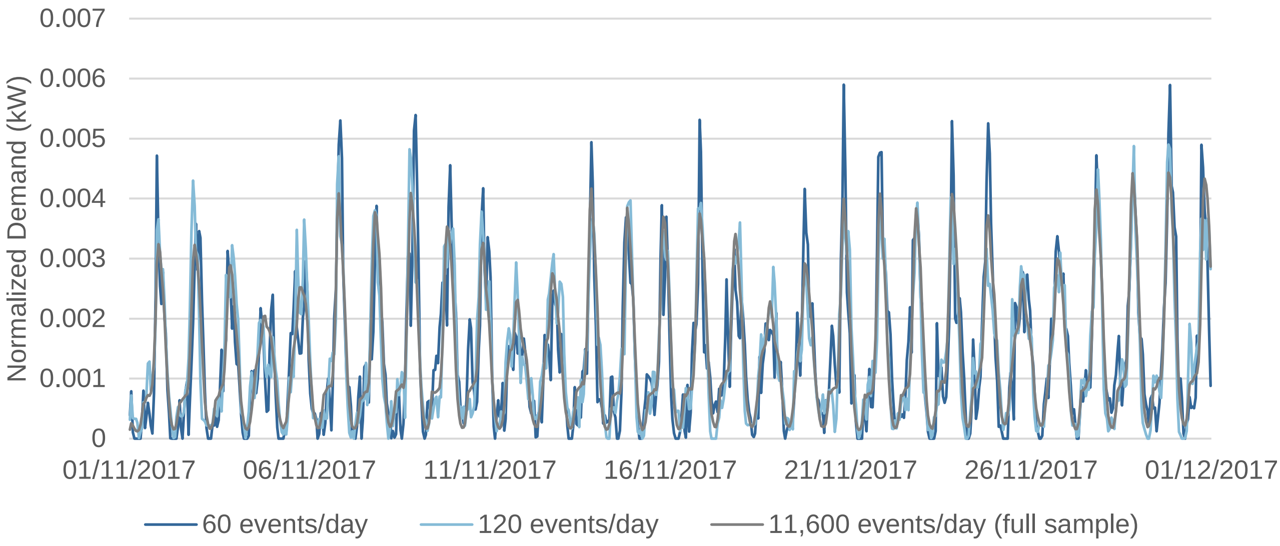

Figure 4-13: Residential demand profile (November 2017) for the full data sample, and sub-samples with an average of 120 and 60 charge events per day.

In addition to altering the peak size, lack of diversity can also impact the peak time. Figure 4-14 shows the demand profiles in Figure 4-13 for a single day only (8th November 2017). Here it can be seen that with a sub-sample of 120 events/day the resultant demand profile is less smooth than the full sample, with a slightly higher peak shifted forward by 1 hour. At 60 events/day, the profile shape is very different, with a large shift in the peak time to between 10-11pm, and a local minimum during the peak in the full sample profile.

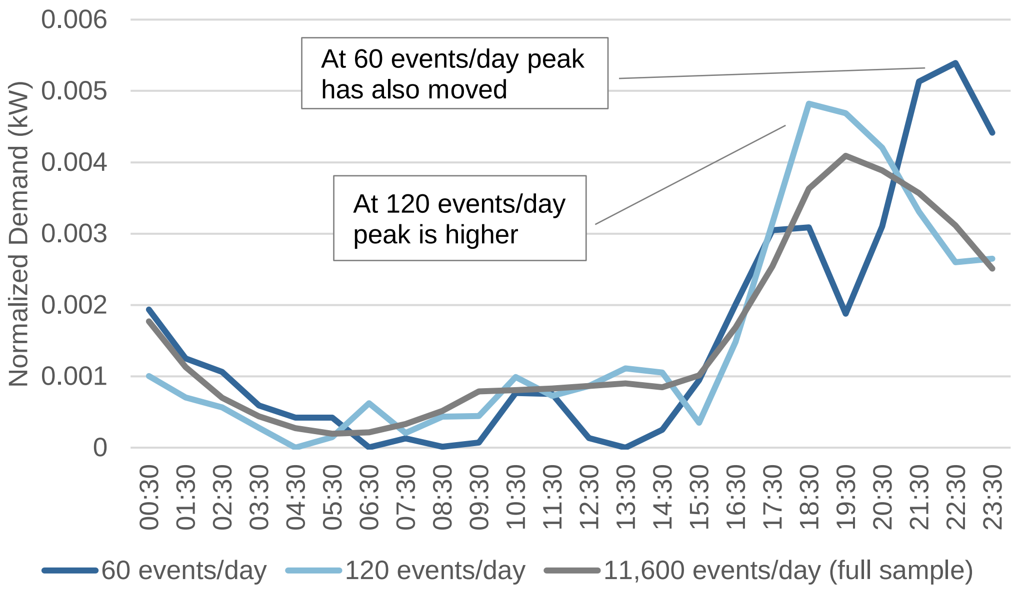

Figure 4-14: Normalized demand profile for residential charging on 8th November 2017 for the full data sample, and sub-samples of 120 and 60 charge events per day.

As part of this study, an analysis has been conducted to quantify how the sample size, in terms of number of charge events per day, affects demand profile diversity (see Appendix 6.6 for details). This has estimated the minimum number of charge events per day, for each charger type, required to ensure profile diversity. These thresholds are shown in Table 4-1, and compared against the events per day for each distribution network licence area. This analysis reveals that for residential charging, the volume of data is large enough to successfully produce diversified profiles for each distribution network licence area, but for the other charger types, this is not possible for several of the licence areas, particularly North Scotland and South Wales.

Table 4-1: Average charge events per day for month with fewest charge events, for each DNO Licence Area*. Sample sizes lower than the estimated diversity threshold are highlighted in amber/red.

DNO License Area	Residential	Work	Slow/Fast Public
E. Midlands	3244	496	731
Eastern	4602	401	723
London	1070	215	928
Merseyside & N. Wales	912	107	45
Midlands	2438	254	411
N. Scotland	553	19	10
N. Western	1623	172	82
Northern	1183	121	146
S. Eastern	2534	207	306
S. Scotland	1404	95	31
S. Western	1440	132	222
South Wales	714	30	64
Southern	3982	630	612
Yorkshire	1479	167	97
Events per day to ensure diversity	**162**	**73**	**176**

**DNO License Area sample sizes have been multiplied by a factor of 4, since ~4 days contribute to each Day Archetype.*

4.5.2 DNO Licence Area Demand Profiles

The following section shows the resulting demand profiles for each distribution network licence area, across the charger types. Note that each profile is shown representative of an average EV at GB level (i.e. the area under each line is the same), and so does not account for differences in mileage or share of charging across charger types between the individual licence areas. Therefore, conclusions can only be drawn from the relative shapes of the profiles, rather than the magnitude. In reality, the profiles may be scaled higher or lower relative to one another.

Residential

Figure 4-15 shows the weekly demand profile for residential charging, averaged over the full year, for each distribution network licence area.

Apart from London, all licence areas show a similar demand profile shape, whereas the evening peak in London is noticeably lower. Since this evening peak is largely due to commuters plugging in after arriving home from work, it is likely that the lower peak in London reflects both the smaller share of cars used for commuting and the lower average commute distance of Londoners in relation to other parts of GB. At weekends, the London profile is much closer in shape to the other licence areas, when the influence of commuting behaviour is low.

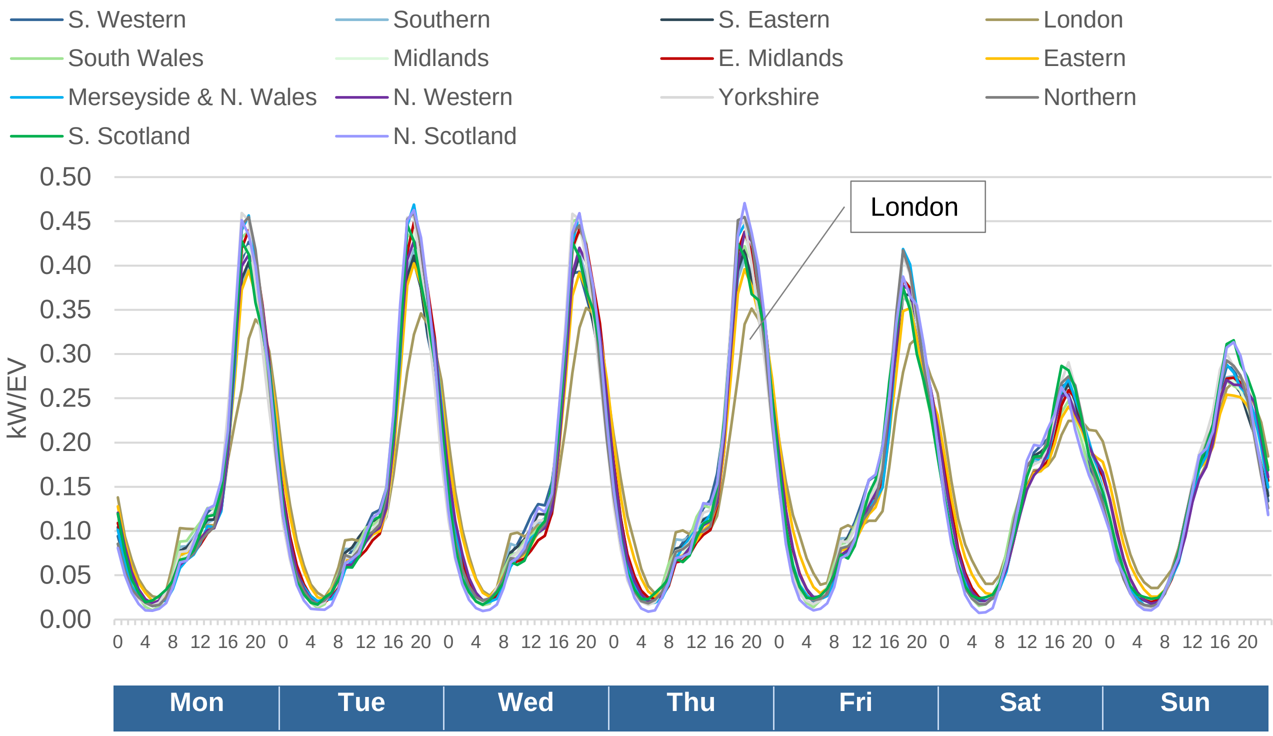

Figure 4-15: Weekly demand profile, averaged over full year, at DNO licence area level for residential charging for an average EV (1,760 kWh/year, receiving 75% demand from residential).

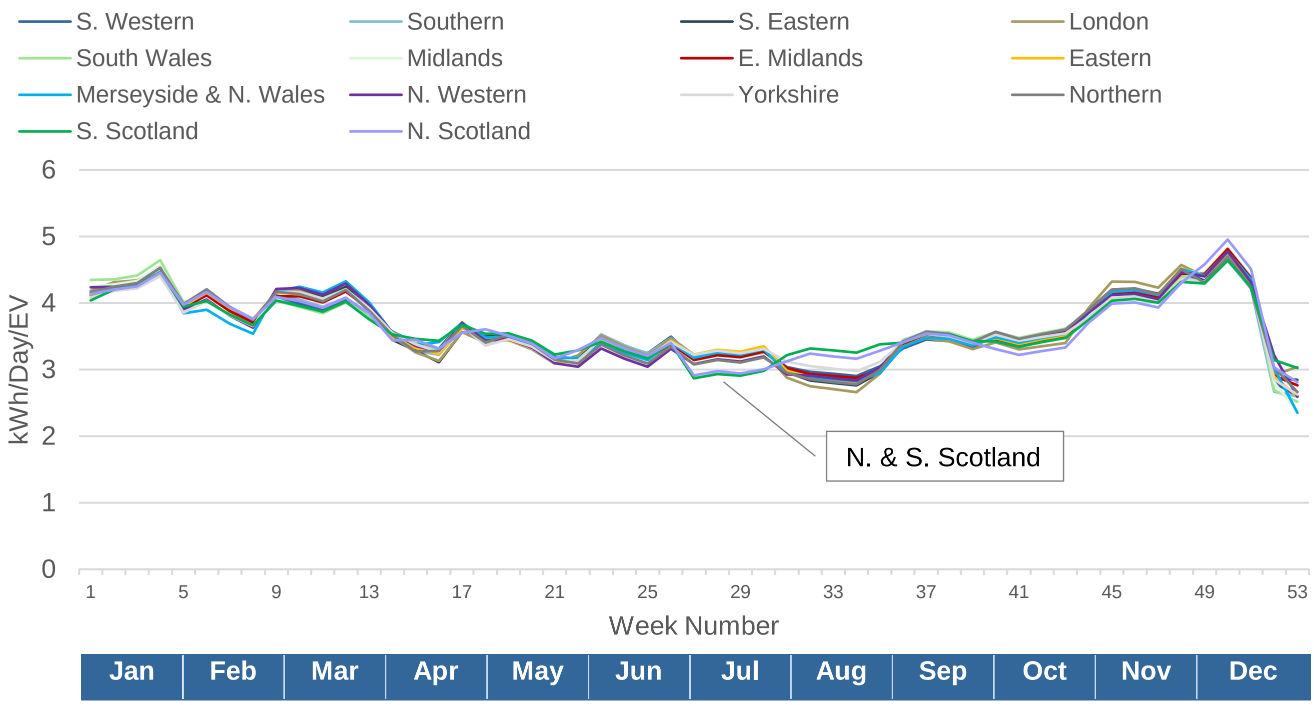

Figure 4-16: Average daily demand for each week over the year, at DNO licence area level for residential charging for an average EV (1,760 kWh/year, receiving 75% demand from residential).

In Figure 4-16 the trend in daily demand over the course of the year is shown (displayed as a weekly average to enable clear comparison between the licence areas). All licence areas appear similar, apart from a reduction in demand in both North and South Scotland in July, relative to the other licence areas. In August, the trend is reversed and North and South Scotland show higher relative demand. This is likely to be a reflection of the school summer holiday, which in Scotland starts in the first week of July, whereas in England and Wales it starts in the fourth week of July.

Work

Figure 4-17 shows the average weekly demand profile for work charging, for each of the distribution network licence areas. Note that the charging event sample size for North Scotland and South Wales are below the diversity threshold shown in Table 4-1.

As for residential charging, the profile shape is similar across all licence areas apart from London, which shows a significantly reduced morning peak on weekdays. Due to the lower share of car driving commuters in London and reduced mileage, it is possible that these charge points are used more commonly by visitors who arrive throughout the day, compared with the rest of the country. Alternatively, due to space constraints in London, more of these work charge points may be shared between employees who are therefore more likely to vacate the charge point during the working day to allow someone else to charge.

The Northern profile also shows a slightly lower morning peak, as well as a second peak in the afternoon between 3-4pm. It is proposed that this may be due to shift workers arriving to begin day and night shifts.

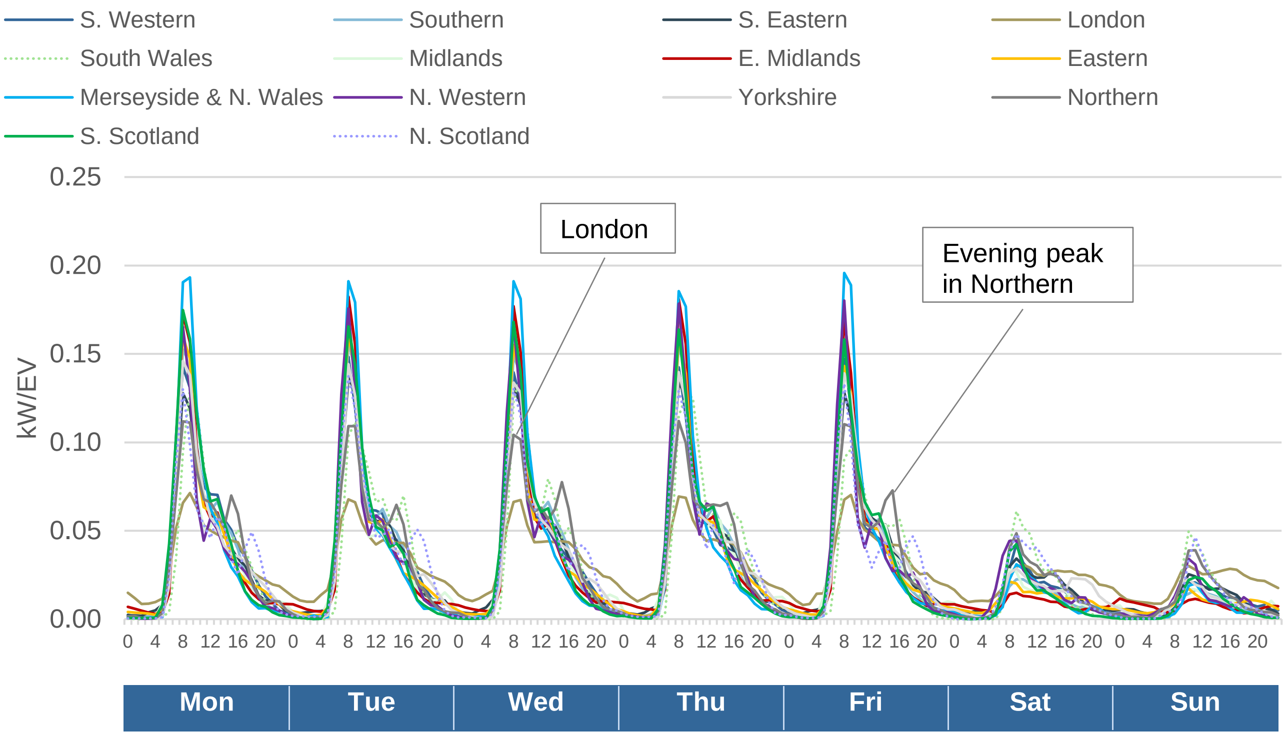

Figure 4-17: Weekly demand profile, averaged over full year, at DNO licence area level for work charging for an average EV (1,760 kWh/year, receiving 15% demand from work). Dotted line denotes sample size is below diversity threshold.

Daily demand across the year shows similar trends in each distribution network licence area, although, there is significant variation in demand during January. Reduced demand in July and higher demand in August is observed for South Scotland, similar to residential charging. The same trend is not observed for North Scotland, however, the sample size is well below the diversity threshold.

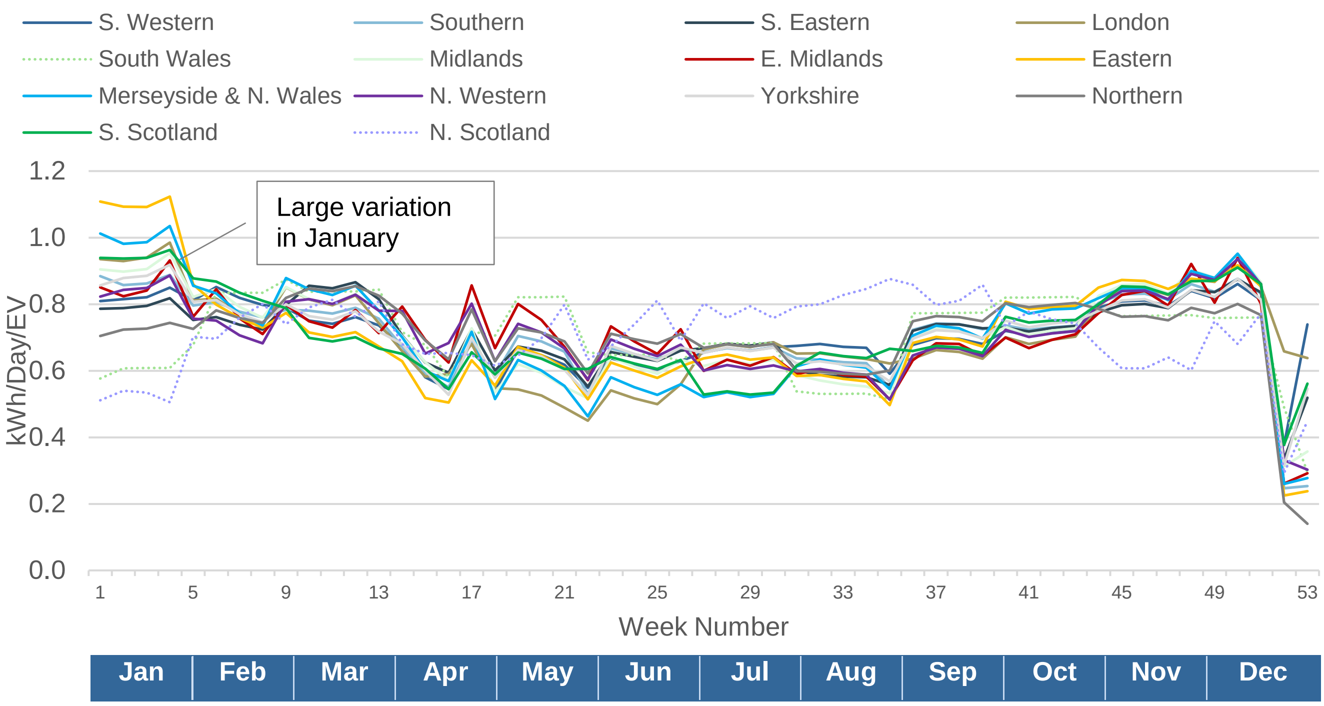

Figure 4-18: Average daily demand for each week over the year, at DNO licence area level for work charging for an average EV (1,760 kWh/year, receiving 15% demand from work). Dotted line denotes sample size is below diversity threshold.

Slow/Fast Public

The average weekly demand profile for slow/fast public charging at distribution network licence area level is shown in Figure 4-19. The charging database includes enough events to generate a diversified profile for only 7 of these licence areas.

East Midlands, South Wales and North Scotland show a larger morning peak than the other licence area, although the latter two are below the diversity threshold. This high morning peak suggests that a large proportion of these charge points are used by commuters. This could be because they are located at train stations or at/near work places.

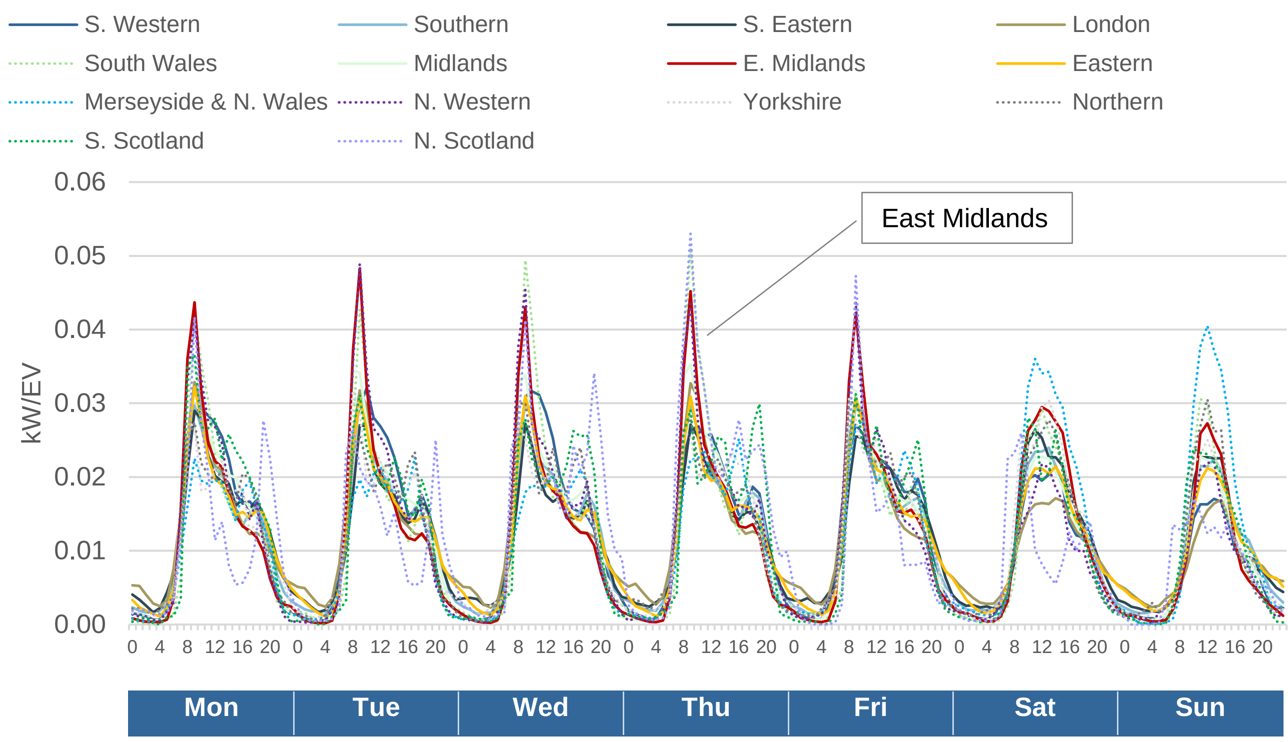

Figure 4-19: Weekly demand profile, averaged over full year, at DNO licence area level for slow/fast public charging for an average EV (1,760 kWh/year, receiving 6% demand from slow/fast public). Dotted line denotes sample size is below diversity threshold.

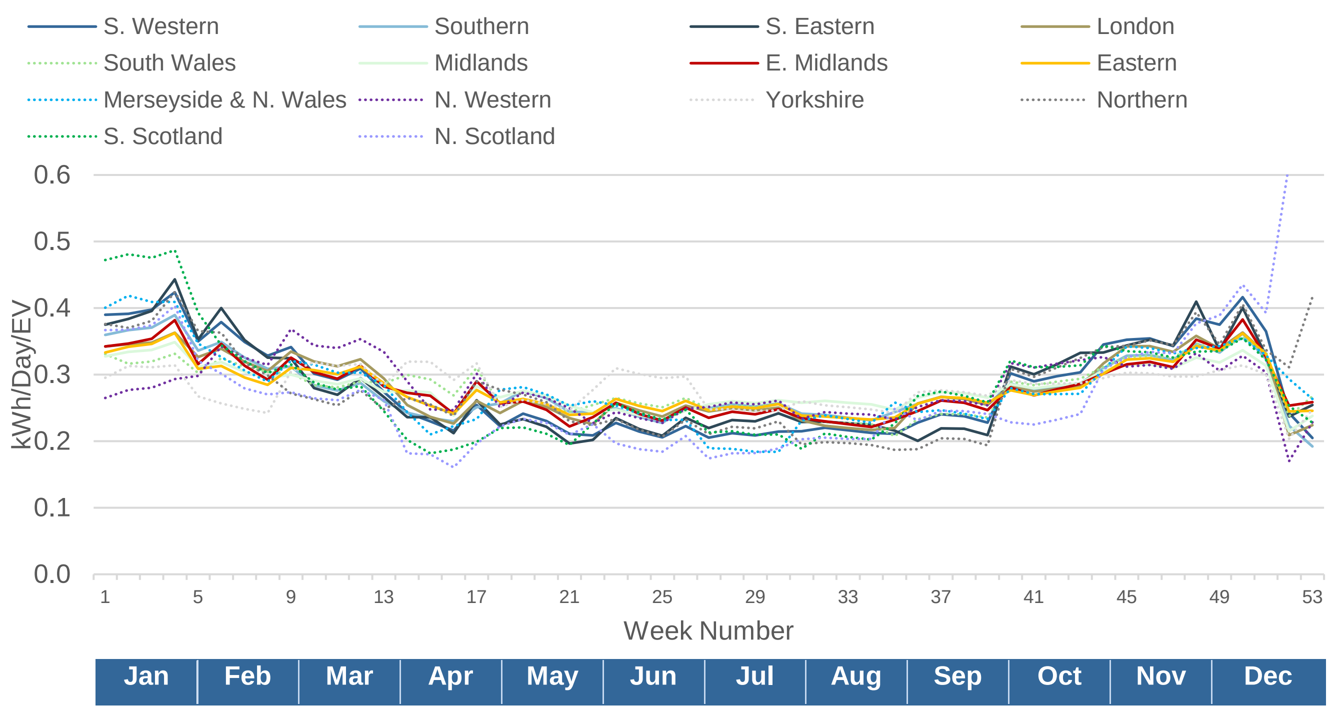

Figure 4-20: Average daily demand for each week over the year, at DNO licence area level for slow/fast public charging for an average EV (1,760 kWh/year, receiving 6% demand from slow/fast public). Dotted line denotes sample size is below diversity threshold.

The trend in daily demand across the year for slow/fast public charging appears similar across licence areas, (see Figure 4-20). There is a sharp increase in daily demand in North

Scotland during January, however this is almost certainly a consequence of a lack of diversity since there are only 16 charge points from this region in the database.

4.6 The Beast from the East

At the end of February 2018, and into the beginning of March 2018, Great Britain experienced heavy snow during the so-called 'Beast for the East' storm. This caused widespread traffic disruption and large numbers of roads were closed due to snow. This resulted in a considerable reduction in charging demand, as fewer trips were made by EV owners. Figure 4-21 to Figure 4-23 show the impact of this snow storm on charging demand at each of the charger types. Note that these are normalized profiles, and thus do not represent the relative contribution of each charger type. They are intended to illustrate the impact on charging demand for each charger type individually.

For all four charger locations, a sudden fall in demand is observed during Monday 26th February and Saturday 3rd March, which coincides with days when it was snowing. Daily demand on Friday 2nd March at all charger types is approximately 40% lower compared with the preceding and following Fridays, despite the temperature being an average of 4°C lower over the course of the day. For work and slow/fast public the decline occurs immediately on Tuesday 27th February, and a day later for residential charging. Reduced demand also persists on Sunday 4th March, after the snow stopped falling, but presumably remained on the roads.

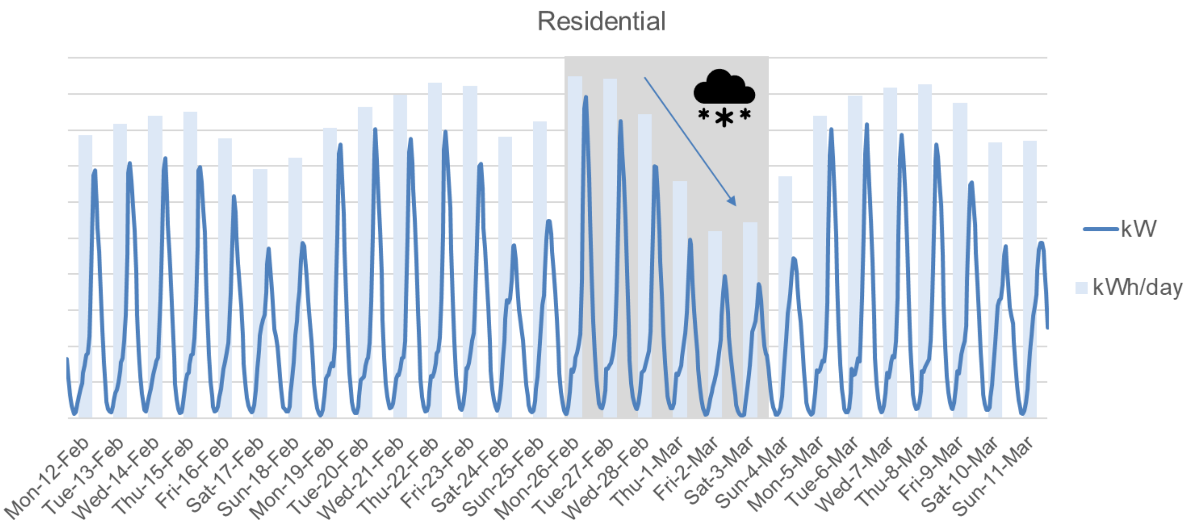

Figure 4-21: Normalized demand profile for residential charging during the 'Beast from the East' storm.

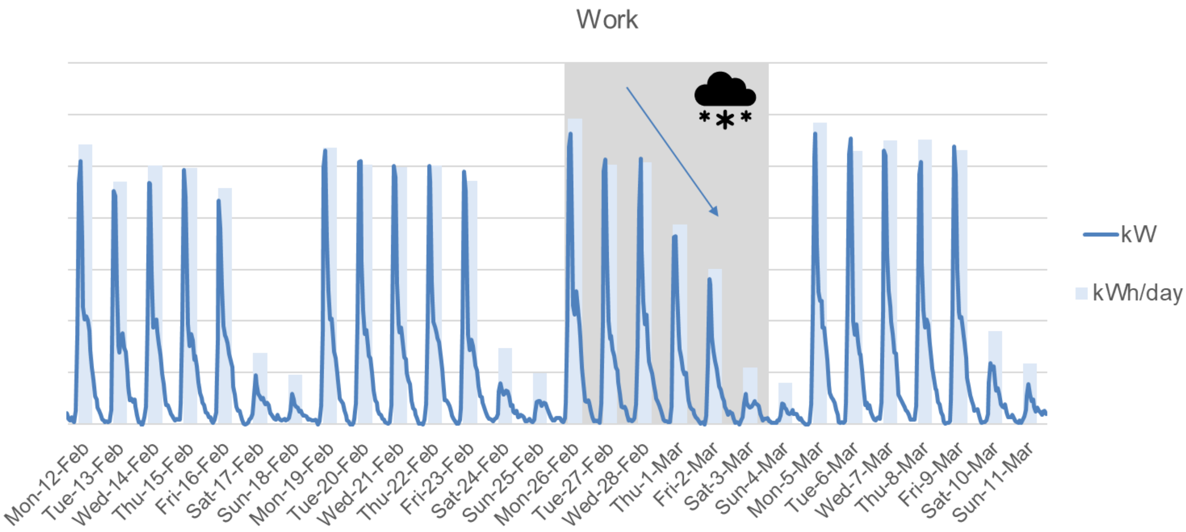

Figure 4-22: Normalized demand profile for work charging during the 'Beast from the East' storm.

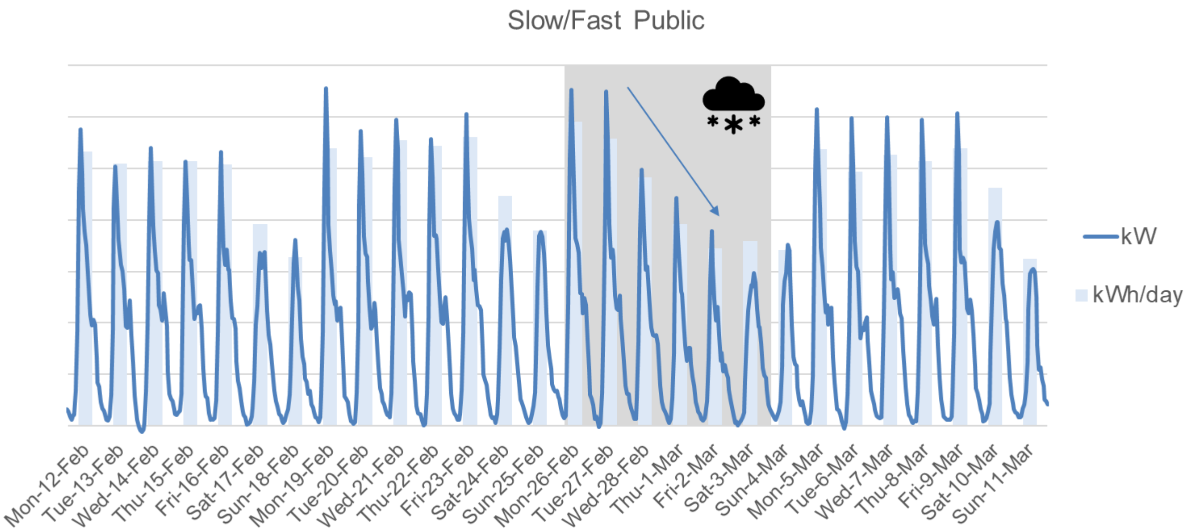

Figure 4-23: Normalized demand profile for slow/fast public charging during the 'Beast from the East' storm.

5 Conclusions and Future Work

5.1 Summary of Findings

This study has for the first time collected together enough GB charging data to develop a high resolution 8,760 charging demand profile, which improves considerably the modelling of EV charging load on the GB electricity system. This has demonstrated a number of key charging characteristics:

- At GB level, unmanaged charging demand currently peaks between 7pm and 8pm on weekdays and is dominated by residential charging demand.
- Work and Slow/Fast Public charging contribute a smaller secondary peak on weekdays in the mid-morning between 9am and 10am.

- Weekend demand is on average 24% lower than weekdays, on a kWh/day basis, with a broader demand profile shape that peaks an hour earlier than on weekdays.
- Temperature has significant impact on demand, particularly residential demand where average kWh/day was found to increase by 1.6% for each 1°C fall in temperature.
- During public holidays, demand is found to be lower than expected, particularly during the Christmas period.
- Heavy snow, which causes travel disruption, is found to significantly reduce charging demand across all charger types.

5.2 Study Limitations

Although this project has aggregated what is believed to be the largest collection of GB charging data to date, there are a number of limitations which could be addressed if this work is updated in future, particularly as the volume of available charging data continues to grow:

1. This study covers only 2 years of data, which makes identifying characteristics that repeat every year (e.g. anomalous days/periods) inherently challenging. The addition of future years will help address this.
2. The event data collected records in most cases only plug-in and plug-out times, and charge start and end times must be estimated. This means the calculated demand profiles may differ from reality, particularly where the EV driver has used a charging delay function to charge during off peak hours (e.g. with Economy 7). Charge point operators reported that they did not record charge start and end times. Other data sources should therefore be explored that may include this information, for example, the vehicle OEMs.
3. The number of charge points present on each day was inferred by identifying the first and last charge events of each individual Charger ID. This provides only an approximation since charge points may have been present but unused outside of these dates, or may have been out of service for some days within these dates. Future data requests should also ask for the number of charge points online on each day.
4. The final demand profiles are provided on a normalized (1 kWh/yr) basis. This provides the flexibility to investigate the impact of different shares of demand across the four charger types. However, in order to generate a demand profile for today, a number of assumptions must be made about current share of charging and total electricity consumption of the EV stock. Future work should attempt to establish accurate figures for share of charging across charger types, for example, by sourcing charging and location data from individual EVs. This is particularly important for understanding the differences between distribution network licence areas, where annual mileage and share of charging across charger types may differ.
5. Despite the large volume of data, there are too few charge events in some distribution network licence areas to generate diversified profiles, particularly for work and slow/fast charging.
6. The profiles generated by this study are indicative of charging behaviour for the stock of EVs on the road today. However, these drivers are early adopters whose charging behaviour may not be representative of future mass market EV owners. For example, the following developments are likely to change overall demand:
    - Changing BEV/PHEV ratio
    - A greater proportion of higher range EVs

- A greater share of EVs without home charging, who must rely on public and work charging. The preferred charging location of these EV drivers is uncertain.
- Adoption of smart charging and battery storage
- Adoption of automated and shared electric vehicles

5.3 Opportunities for Further Work

This study was initiated with the intention to generate an accurate 8,760 demand profile for EV charging today (2018). However, in the process a large and highly valuable charging dataset has been created which provides opportunity to investigate further aspects of charging demand. Possible examples include:

1. Exploring further insights:

This study has made an initial assessment of influencing factors on charging demand (e.g. weekday, temperature, bank holidays). Additional analysis would reveal further factors (both regular and extreme) that could be used to better forecast charging demand.

2. Stress testing:

Following on from 1), identifying the major influencing factors would enable “stress testing” of the network in response to extreme weather patterns.

3. Looking forward to 2030:

As EV volumes grow over the next decade there is potential for considerable changes in the EV fleet (e.g. EV ranges, BEV/PHEV ratio, higher charging rates, preferred charging location etc.) which will influence the overall charging load.

4. Exploring flexibility and system benefits:

The demand profiles in this work are assumed to be unmanaged, but the charging event data can be used to quantify the availability of charging EVs, and thus explore the extent of the flexibility in this demand signal (e.g. to minimise load for DNOs, respond to weather/renewable energy output).

5. Impact of other electric vehicle types:

This study has captured the charging demand of plug-in cars, but as other vehicle segments electrify this will add to demand. This, for example, includes depot-based vans, HGVs and buses that may show different demand profile characteristics.

6 Appendix

6.1 Summary of charge event data

This study aggregated a dataset of over 8.3 million charge events. Table 6-1 summarises the contribution of the various data sources used.

Table 6-1: Summary of charge event data from each data provider after cleaning.

Charger Type		OLEV	Other Providers	Total
Residential	# Events	3,105,310	3,236,479	6,341,789
	First Event	01/01/2017	01/01/2017	
	Last Event	31/12/2017	31/12/2018	
Work	# Events	41,261	412,518	453,779
	First Event	01/01/2017	11/01/2017	
	Last Event	31/12/2017	31/12/2018	
Slow/Fast Public	# Events	49,926	571,926	621,852
	First Event	01/01/2017	01/10/2017	
	Last Event	31/12/2017	31/12/2018	
Rapid Public	# Events	131,306	789,991	921,297
	First Event	01/01/2017	02/01/2017	
	Last Event	31/12/2017	31/12/2018	
				8,338,717

6.2 Issues with data

6.2.1 Data cleaning

Charge events in the raw data which failed to meet the following criteria were considered erroneous and excluded from the analysis:

- Event energy (kWh)
  - For slow/fast charge events (≤22 kW), events must be >0.5 kWh and <100 kWh. 100 kWh was chosen as an upper bound as this is the largest EV battery capacity currently available[5].
  -
- Plug-in duration
  - Events must be >3 minutes, as suggested by OLEV in their data cleaning process[6]. This excludes very short charge events which are likely to be

[5] Tesla Model S 100D and Tesla Model X 100D. Note that usable battery capacity is 90-95 kWh, however, this is offset by a charging efficiency of 90-95%, thus maximum energy as measured at the charge point is approximately 100 kWh.
[6] Electric Chargepoint Analysis 2017: *Local Authority Rapids. Notes and definitions.*

because the charge failed or was a test event performed by those maintaining the charge point.
  - No maximum has been placed on plug-in duration. Although a number of charge events are found to have plug-in durations >24 hours, the time spent charging is significantly less than this, and it is this latter quantity which is used to calculate the demand profiles.
- Implied rate [event energy (kWh) divided by plug-in duration (hrs)]
  - For data sources, events must have an implied rate less than or equal to rated charger speed (e.g. 22kW, 7kW, 3.6kW)

In addition to the above steps, duplicate events in each data source were removed. This cleaning process excluded 6.6% of charging events in the raw data (see Table 6-2).

Table 6-2: Summary of number of charge events excluded from each data source during data cleaning.

Dataset	Events in raw data	Events excluded	Events after cleaning
OLEV	3,684,088	336,417	3,347,671
Other sources	5,260,719	249,805	5,010,914
	8,944,807	**586,222**	**8,358,585**

After adding cleaned charge event data to the database, events which were duplicated in multiple sources were identified, with the duplicates removed. This resulted in the exclusion of 15,101 residential, 122 work and 4,645 slow/fast public charge events from the cleaned OLEV data.

6.2.2 Identifying work charge points

For some datasets, identifying work charge points was challenging because where work places are publicly accessible, there is some overlap with the definition of slow/fast public charge points. In the data received each charge point was labelled with one of 16 different location classifications. The share of events starting in each hour for 8 of these classifications is shown in Figure 6-1. Those classified as *'Private Carpark'*, '*Dealership*', and *'Education/Health'* appear very similar to '*Work'* and so have been classified as work charge points.

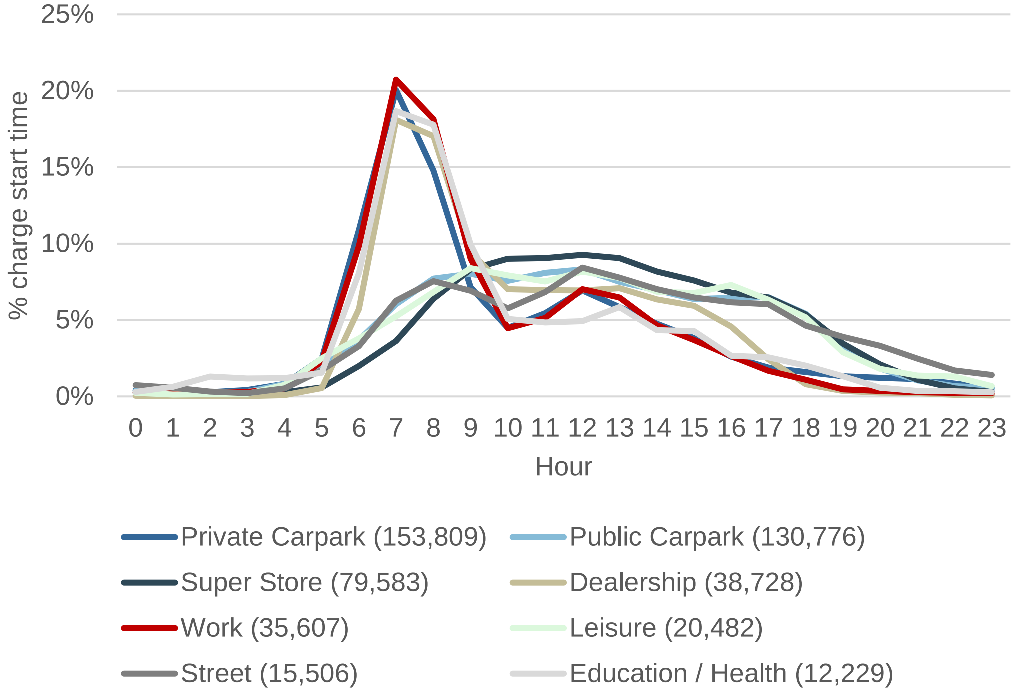

Figure 6-1: Share of charge events starting in each hour for each slow/fast public and work location type in the data.

Likewise, the OLEV data includes a classification called 'Public Sector Fasts'. These are charge points that have been funded by OLEV and are publicly accessible. However, this includes charge points that have been installed at sites where a large number of people work, for example hospitals, which might be better described as work place charge points rather than slow/fast public. Consequently, OLEV Public Sector Fasts charge points that display a large morning peak in charge event starts have been classified as work charge points. Figure 6-2 shows how the resulting share of events starting in each hour appear very similar to work charge points.

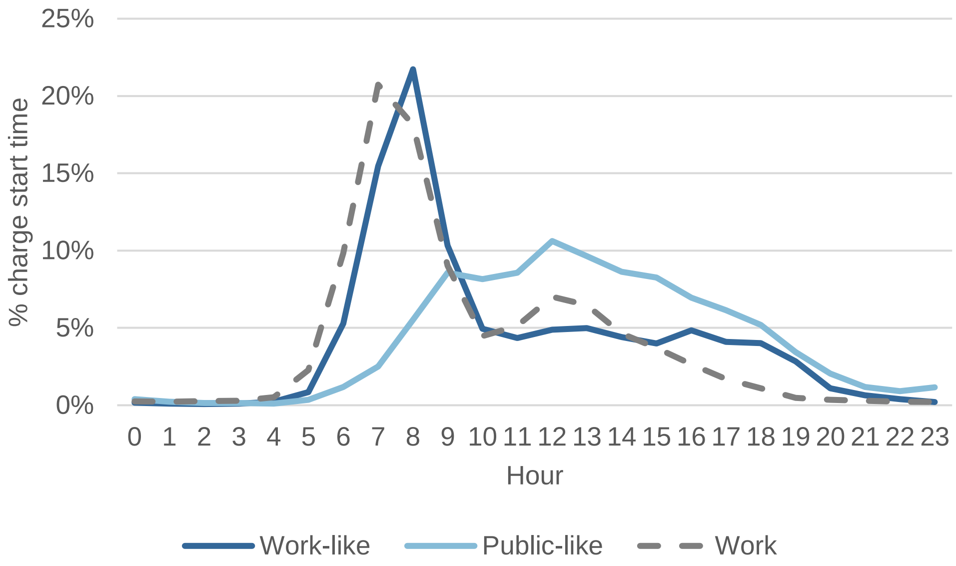

Figure 6-2: Share of charge events starting in each hour for OLEV Public Sector Fasts charge points, compared with work charge point.

6.2.3 Estimating number of charge points over date range in OLEV Residential data

The OLEV Residential data was collected quarterly, which leads to two issues:

- The number of charge points in each quarter changes (see Figure 6-3), resulting in large differences in average kWh/day between quarters
- Charge events that straddle two quarters are not included in the raw data, which leads to a dip in demand at the end of each quarter (see Figure 6-4)

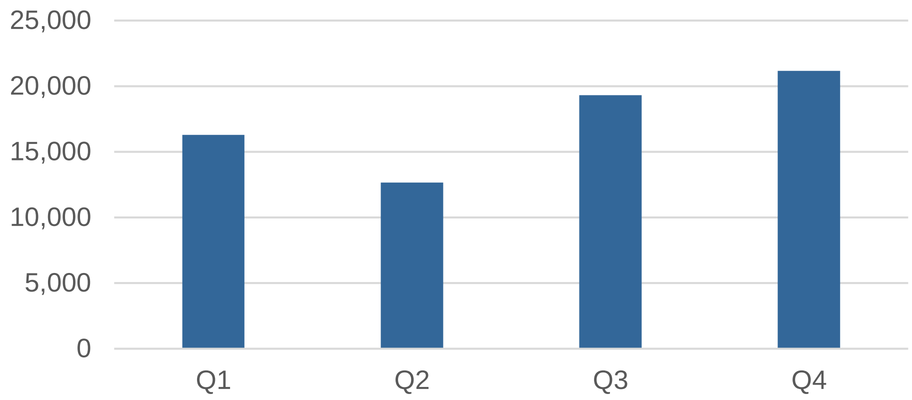

Figure 6-3: Number of unique Charger IDs in OLEV residential charge event data in each quarter of 2017.

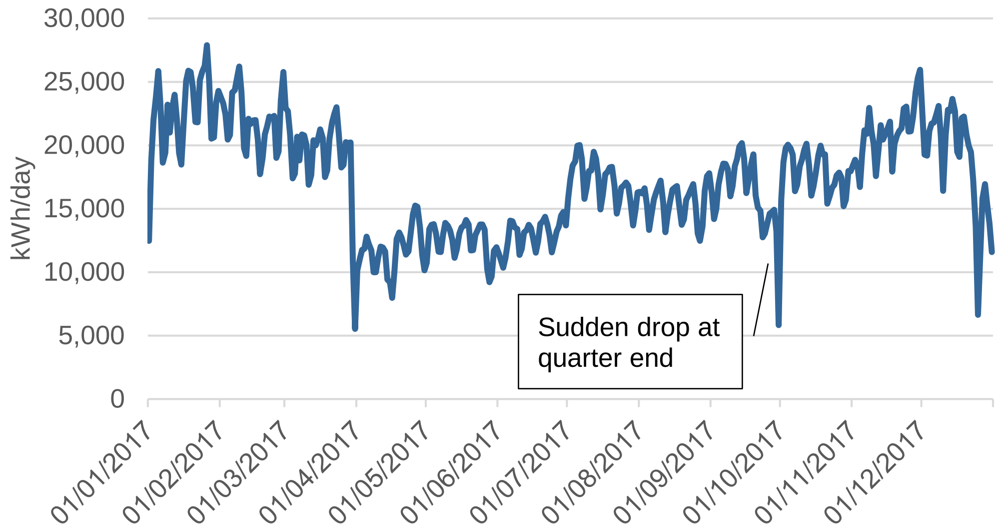

Figure 6-4: Daily demand calculated from raw OLEV Residential charge event data.

To correct for differences between the quarters, two corrections were applied:

- Demand was corrected to per charge point. The number of charge points online was estimated by identifying the first and last charge event of each Charger ID, assuming this was when it entered and left the stock. An additional step was required to estimate the number of charge points at the beginning and end of each quarter, where charge points may have been online but unused. The number of charge points during this period was estimated by interpolating the growth trend either before or after (see Figure 6-7).

- Daily demand on the days before and after the quarter boundaries was corrected to make equal to the average inter-day difference (e.g. difference in demand between Monday and Tuesday)

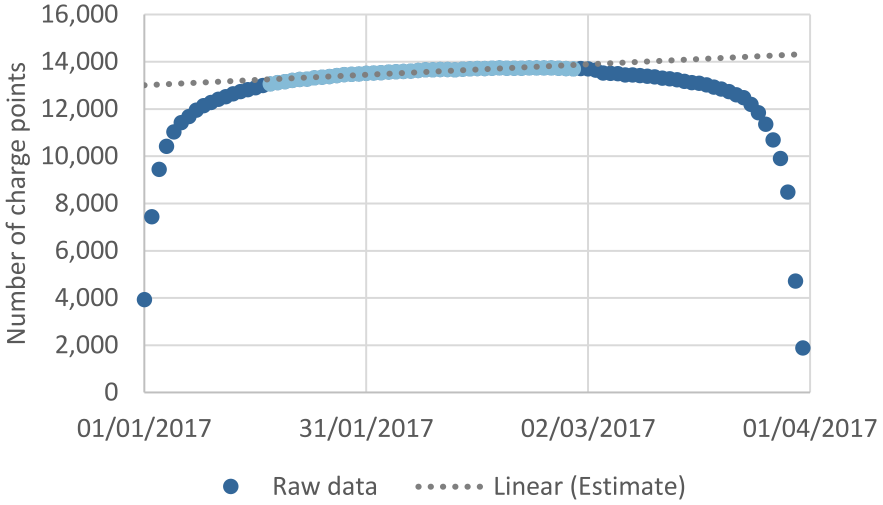

Figure 6-5: Estimate (grey dotted line) for stock of charge points in Q1 2017 in OLEV Residential data.

The resulting daily demand profile after applying these correction stops is shown in Figure 6-6. Note that additional correction steps were applied to remove remaining long-term trends, as outlined in Appendix 6.3.

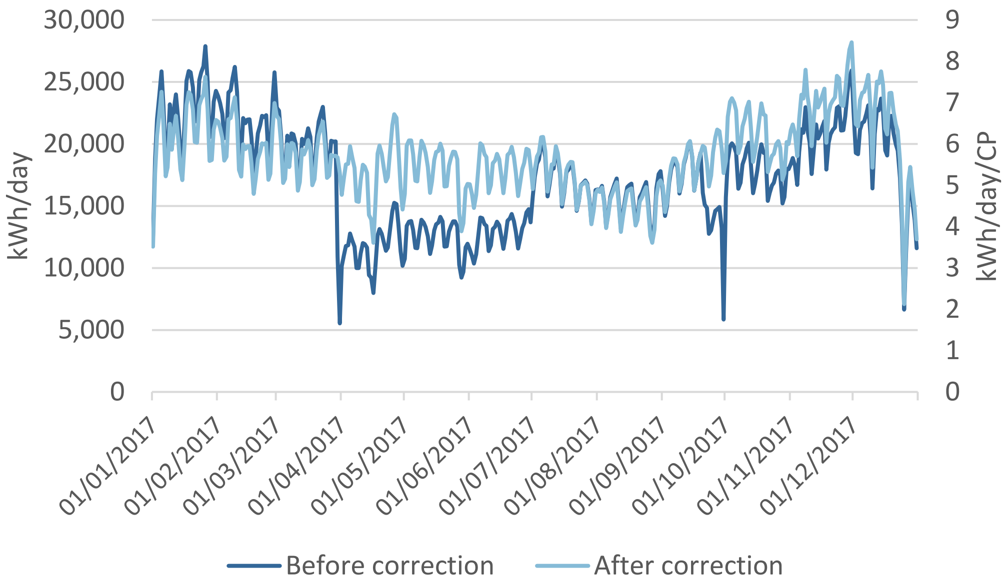

Figure 6-6: Daily demand profile before and after correcting for the different charge point stock in each quarter.

6.3 Generating demand profiles from each data source and correcting for long term trends

The following sections outline how demand profiles were generated from the charging event data of each data source, and processed to remove the influence of long-term demand trends. These had to be removed so that the final demand profiles represented a steady state EV stock.

6.3.1 Correcting demand profiles for growth in number of charge points

It was found that there were significant differences in the demand trends between the different data sources. Some sources consist of a fixed stock of charge points (e.g. OLEV datasets), while for others the stock of charge points is increasing which causes an increasing trend in demand. Therefore, for sources in which a Charger ID is available, the demand profile is scaled by the number of charge points present on each day, thereby converting to daily demand per charge point. The result of this correction is illustrated in Figure 6-7.

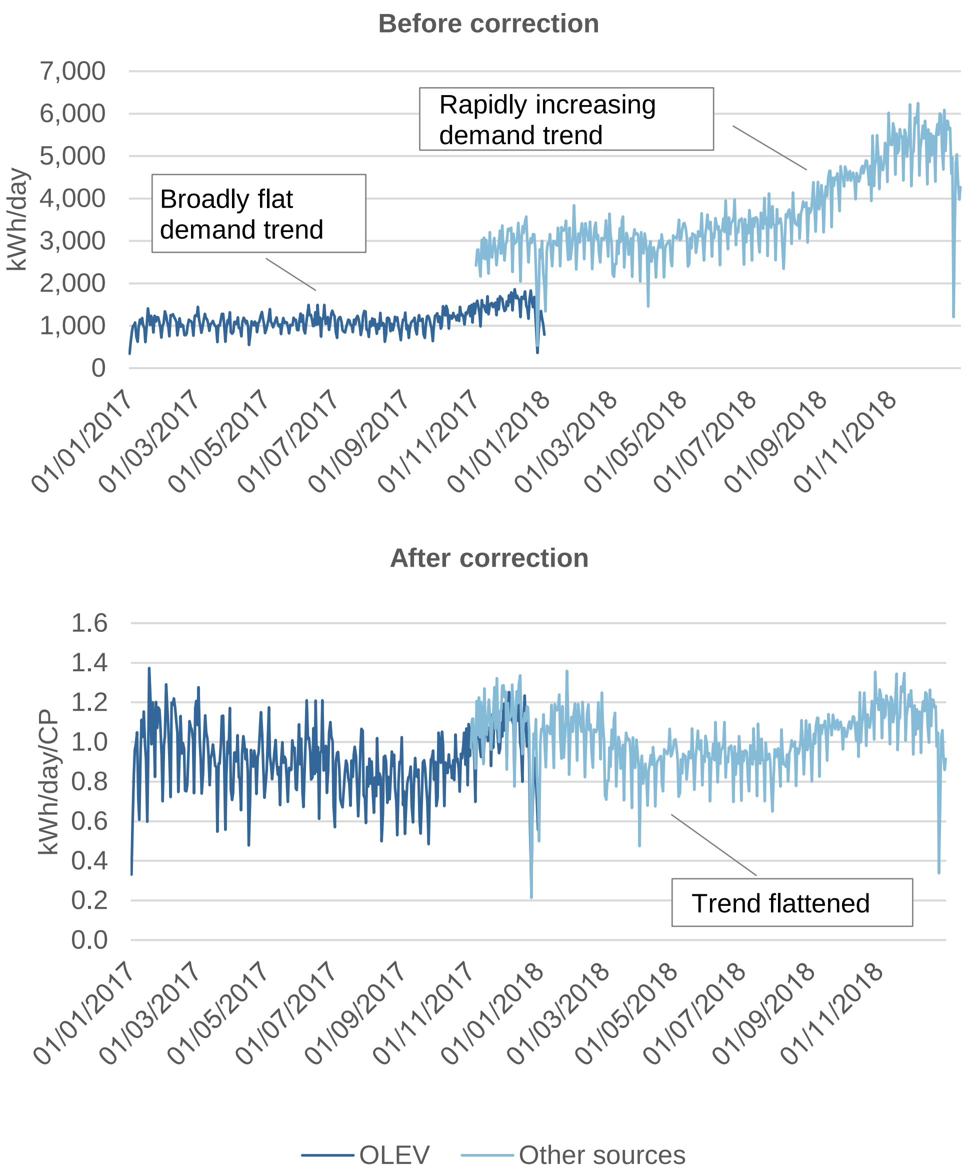

Figure 6-7: Daily demand for slow/fast charging from other sources and OLEV, before and after correction for growth in charge point stock.

The number of charge points present on each day is estimated by identifying the first and last events for each charge point, and assuming this is when the charge point first enters and leaves the stock. During the first and last days of each data source, some charge points are not used at all but are still online. However, this approach leads to these charge points appearing offline and so an estimate must be made for the number of charge points present during these periods by interpolating the trend from following or preceding month.

6.3.2 Correcting demand profiles for increasing number of EVs

As the number of EVs in the UK stock increases, average electricity demand at the shared charge points (e.g. public) grows. Slow/fast public demand profiles are therefore corrected for this increase in the stock of EVs than can use them. Figure 6-8 shows an example of this correction.

Work charge points are shared in theory, however, in all cases a correlation of demand per charge point with the number of EVs was not visible. It is suggested therefore that these charge points are shared amongst a fixed stock of EVs (e.g. 1 or 2 vehicles), with additional charge points added as more employees purchase an EV.

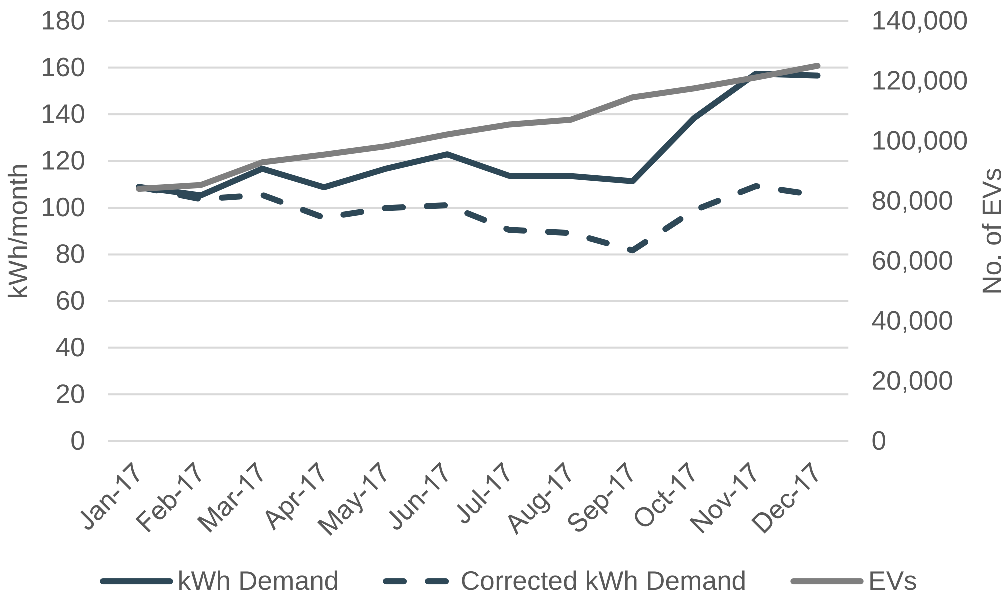

Figure 6-8: Example of correcting the trend in daily demand in OLEV Slow/Fast Public charging data due to growth in EV stock.

6.3.3 Removing the influence of temperature

Electricity demand is found to be correlated with temperature, since EVs tend to use more energy when it's colder. However, in order to remove any remaining long-term trends in the following step, the effect of temperature was identified and removed. This ensures that real trends due to temperature can be added back in. In order to do this, the effect of weekday was first removed from the demand profile and the correlation between the resulting daily demand and average daily temperature established[7]. Figure 6-9 shows an example correlation for residential charging.

[7] Temperature data was sourced from EGNX weather station, East Midlands Airport.

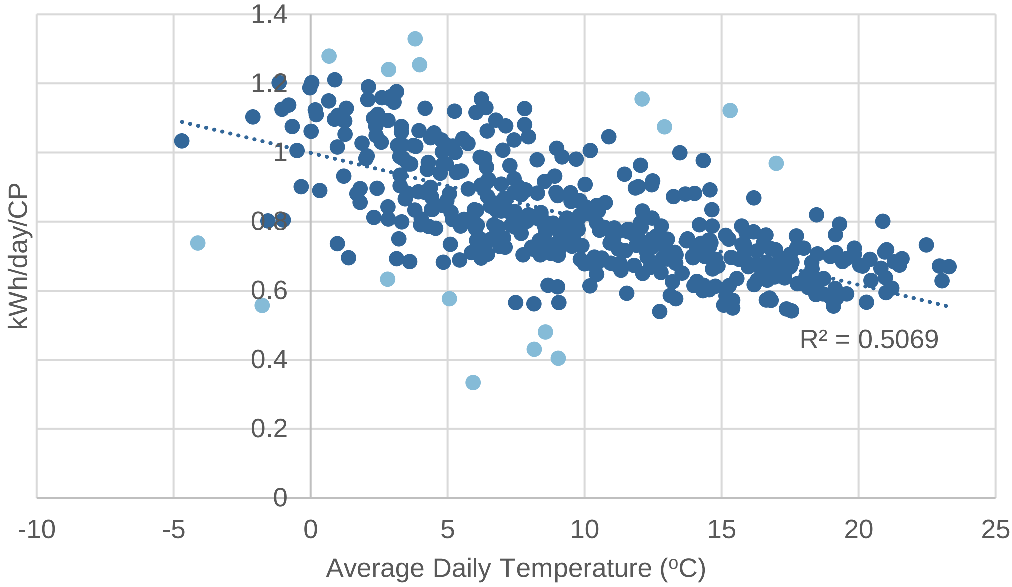

Figure 6-9: Correlation between daily charging demand (corrected for weekday) and average daily temperature, for residential charging. *Light blue dots lie outside of the range Q1 – 1.5 IQR and Q3 + 1.5 IQR, and are excluded.*

6.3.4 Correcting for remaining long-term demand trends

After the influence of temperature was removed, any remaining long-term trends in daily demand are corrected for by rotating the demand profile, such that the trend over the course of the data series is flat. An example of this is shown in Figure 6-10.

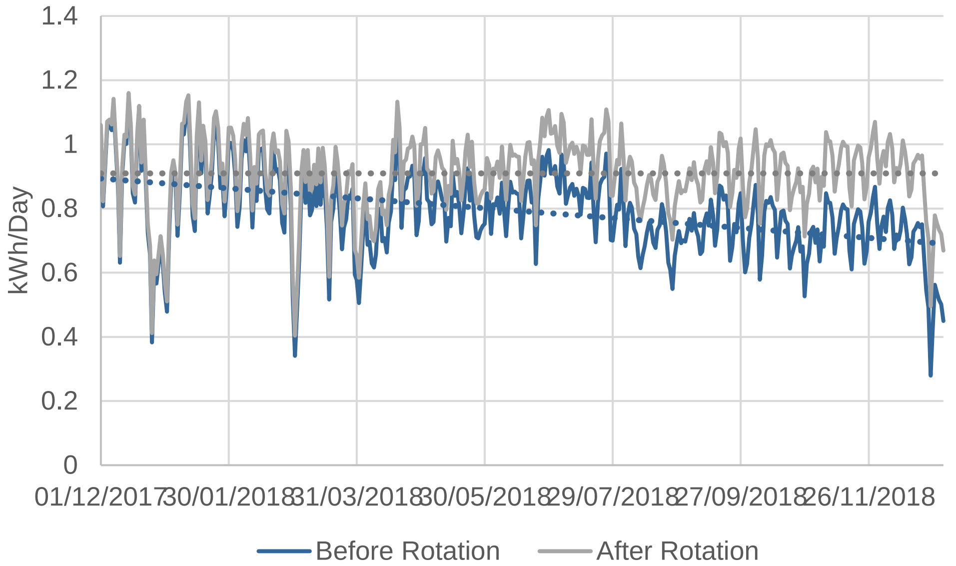

Figure 6-10: Example removal of remaining long-term trends from daily demand profile in residential charging.

6.3.5 Re-introducing the influence of temperature

After all long-term trends have been removed, the influence of temperature is added back into the daily demand profile. An example of this is shown in Figure 6-11.

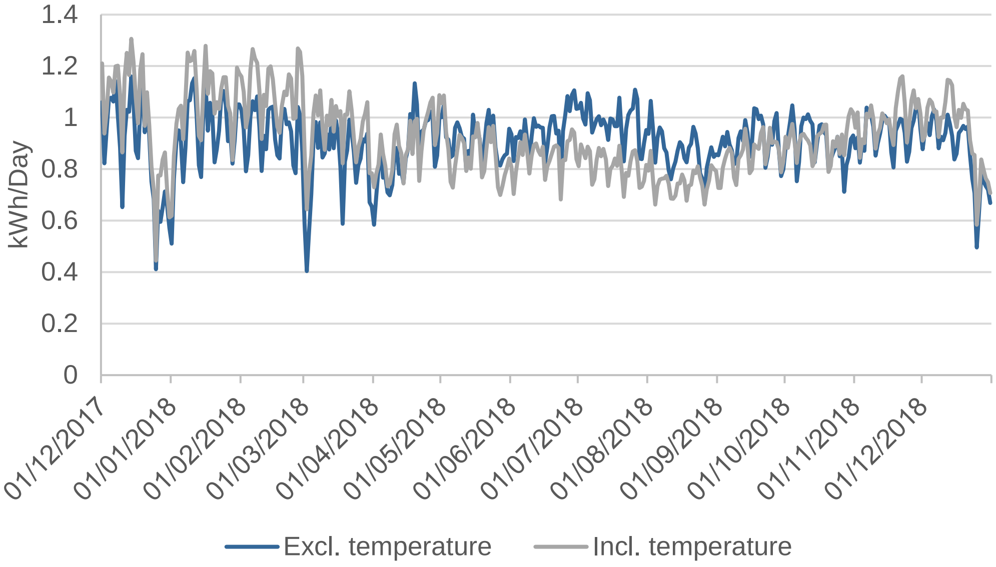

Figure 6-11: Example of the re-introduction of the effect of temperature into residential daily demand profile.

6.3.6 Re-scale profiles to their average daily demand

To ensure profiles from different sources have comparable scales, they were divided by their average daily demand (kWh/day). When profiles are later combined, this avoids one profile disproportionately contributing to the combined profile due to differences in scale.

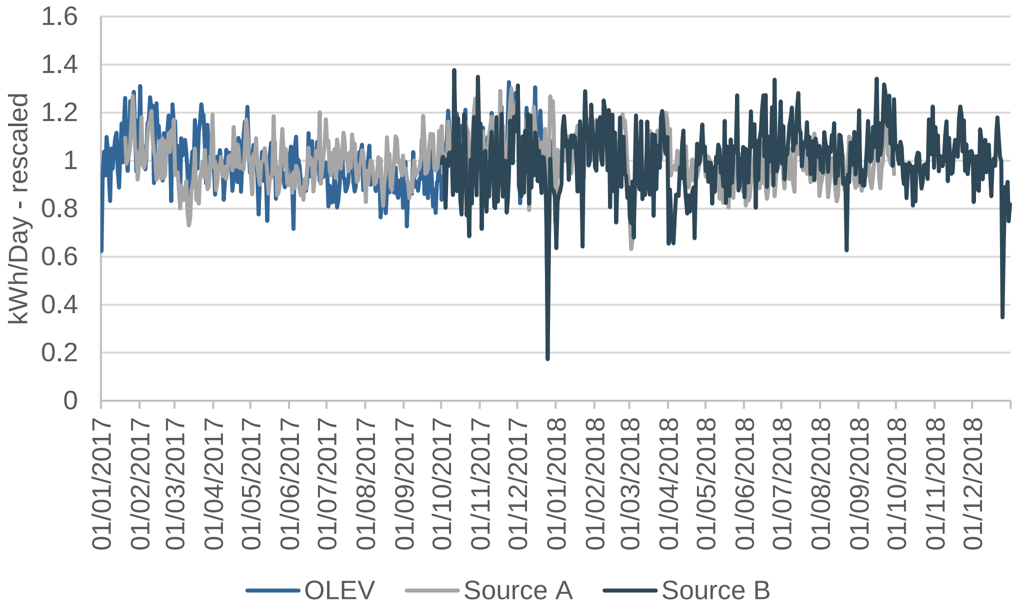

Figure 6-12: Example of daily demand profiles from various sources that have been fully corrected to remove long-term trends and rescaled relative to their average kWh/day.

6.4 Combining demand profiles from each source to create annual demand profiles

The following sections describe the steps for combining the demand profiles from each data source to create a normalized full year hourly demand profile for each charger type.

6.4.1 Combing demand profiles by weight averaging by demand

To generate a combined daily profile for each charger type, the daily demand profiles from each available data source (corrected for long term trends, as described in Appendix 6.3) were combined using a weighted average approach: Before combining, each profile was weighted by its daily demand in the raw demand profiles. This ensures that the combined profile reflects the true contribution of each source to overall demand. This is illustrated in Figure 6-13.

Figure 6-13: Daily demand for charging from raw charge event sources, and the resulting combined profile (red).

6.4.2 Identifying and removing the influence of temperature

Using the method described in Appendix 6.3.3, before correcting for remaining long-term trends, the influence of temperature was established and removed. Figure 6-14 to Figure 6-16 show the resulting correlations between average daily temperature and daily demand (corrected for weekday trends). In all cases the correlation is negative as expected. Residential charging shows the strongest correlation, with an R-squared value of 0.60. The correlation with work charging is fairly weak, with an R-squared value of only 0.18. However, if weekend charging demand, which is considerably lower, is excluded this rises to 0.26.

As well as the strongest correlation, residential charging also appears most affected by temperature. For every 1°C increase in temperature, daily residential charging demand falls by an average of 1.6%.

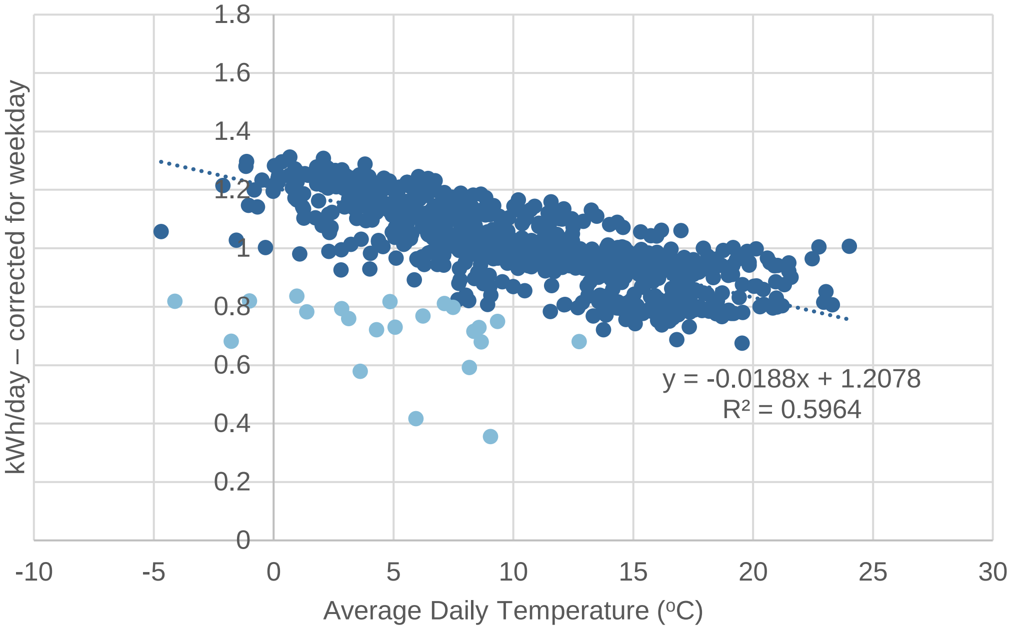

Figure 6-14: Correlation between daily demand, corrected for weekday, and temperature for residential charging. ***Light blue dots lie outside of the range Q1 – 1.5 IQR to Q3 + 1.5 IQR, and are excluded from correlation*.**

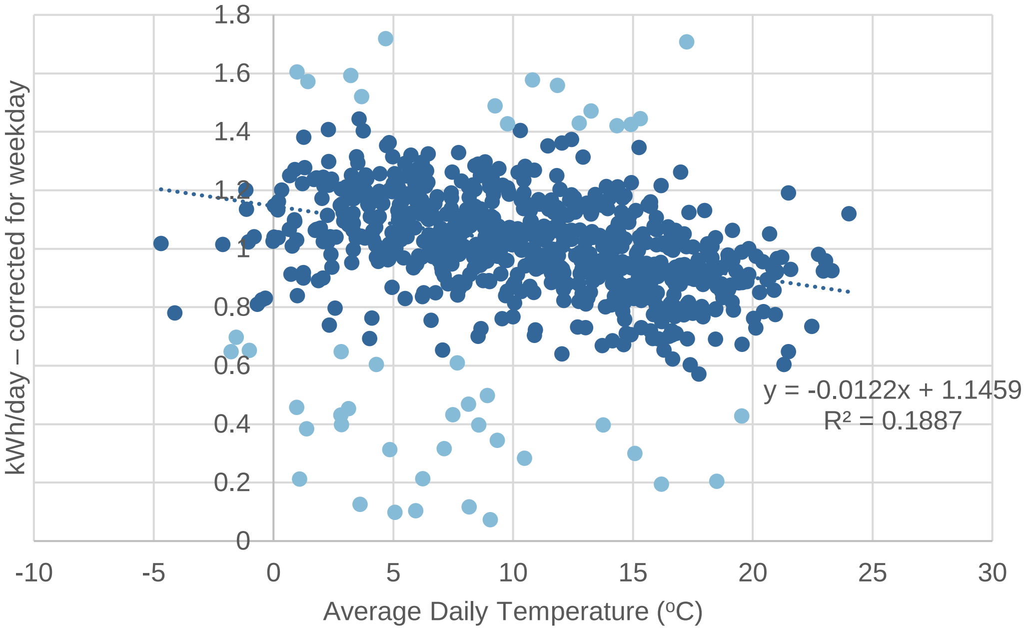

Figure 6-15: Correlation between daily demand, corrected for weekday, and temperature for work charging. ***Light blue dots lie outside of the range Q1 – 1.5 IQR to Q3 + 1.5 IQR, and are excluded from correlation*.**

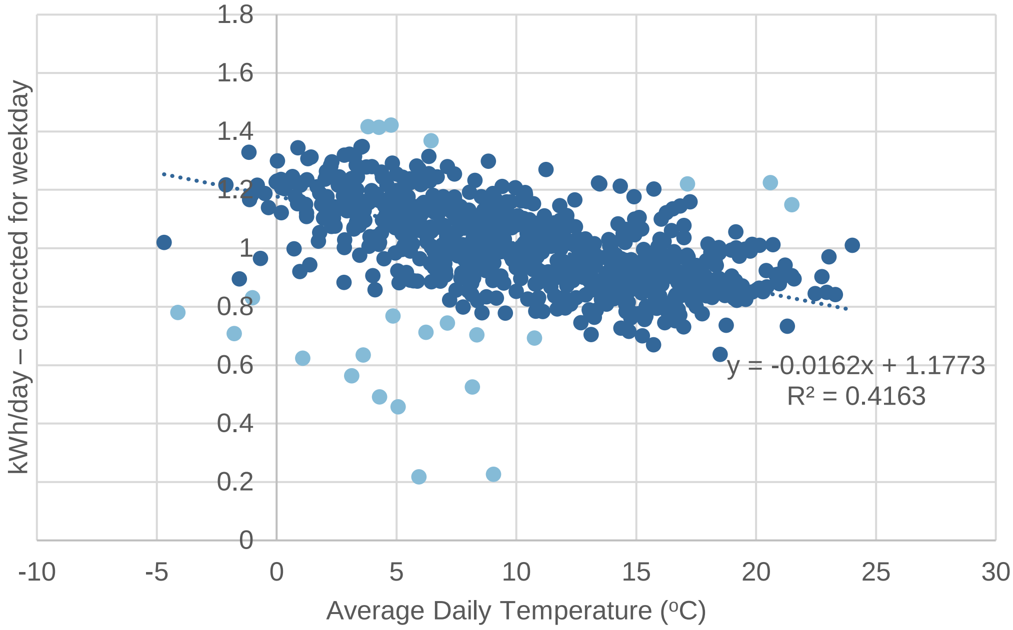

Figure 6-16: Correlation between daily demand, corrected for weekday, and temperature for slow/fast public charging. ***Light blue dots lie outside of the range Q1 – 1.5 IQR to Q3 + 1.5 IQR, and are excluded from correlation*****.**

6.4.3 Correcting for remaining long-term demand trends

Using the approach described in 6.3.4 for individual data sources, after removing the influence of temperature the daily demand profile for each charger type was rotated such that the long-term trend was flat. An example of this, for residential charging, is shown in Figure 6-17.

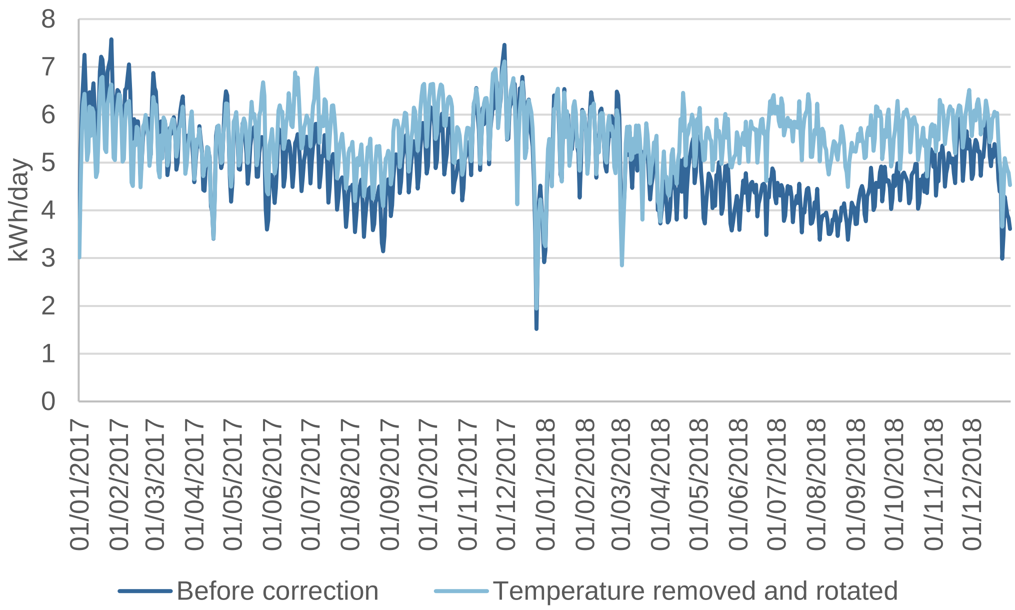

Figure 6-17: Daily demand profile for residential charging before and after influence of temperature is removed and profile is rotated to ensure flat demand trend.

6.4.4 Calculating daily demand for each Day Archetype

The demand profiles of each charger type resulting from the correction steps in Appendix 6.4.3 were aggregated into a series of Day Archetypes. These represent the demand on each weekday within each month (as well as anomalous days, see next section). This aggregation scheme was found to be the best trade-off between reflecting differences in demand throughout the year while simultaneously allowing data from multiple years to be combined. Each Day Archetype has two demand components:

- Daily demand (kWh/day)
- Hourly demand profile (kW) – normalized to 1kWh per day.

In each case, the average of contributing days is calculated, weighted by daily demand from the raw charging event data. This ensures that days later on in the time series when there are more charge events (i.e. 2018) contribute more than days when there are fewer charge events (i.e. 2017). An example normalized hourly demand profile for a Day Archetype is shown in Figure 6-18.

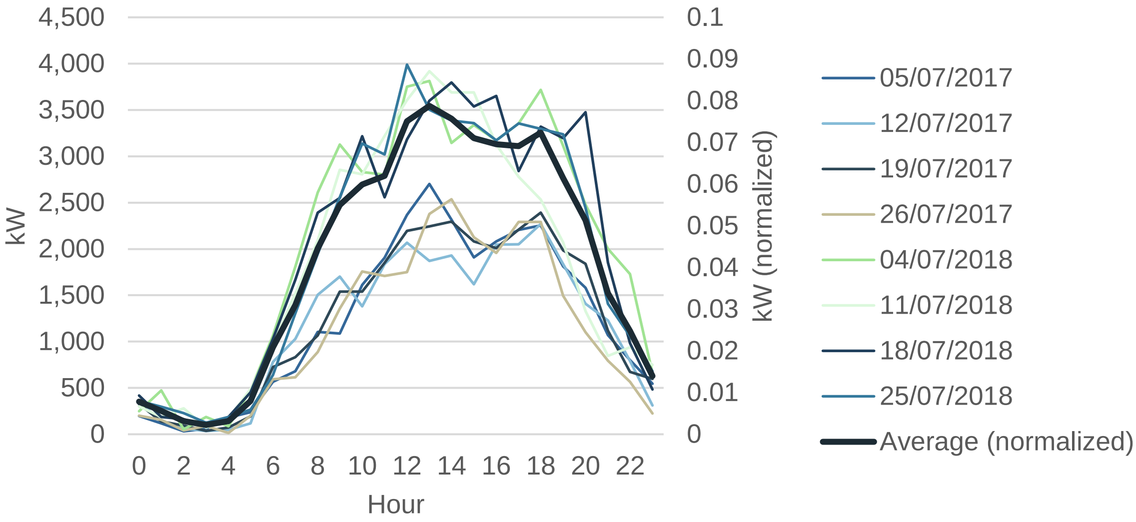

Figure 6-18: Example of normalized hourly demand profile for July-Wednesday Day Archetype, and its contributing days.

6.4.5 Identifying anomalous days

Days of anomalously high and low demand that are not well represented by the Day Archetype of their month and weekday are assigned their own Day Archetype. These anomalous days were identified by comparing the variance between the daily demand on each day that day's Day Archetype. The results of this analysis for each charger type are shown in Figure 6-19 to **Error! Reference source not found.**. Note that in each case, the effect of temperature has been removed, and data coverage is higher in 2018 than 2017.

Days of anomalous demand appear to coincide with public holidays, such as Christmas, Easter and the May and August Bank Holidays. For residential charging, work and slow/public charging, demand is lower than expected during all these days. As a consequence of these findings, the following days were assigned their own Day Archetypes:

- New Year's Day
- Good Friday to Easter Monday
- Early May Bank Holiday Monday

- Spring Bank Holiday Monday
- Summer Bank Holiday Monday
- Christmas Eve to New Year's Day

In addition, as discussed in Section 4.6, the 'Beast from the East' can also be seen to cause a significant reduction in demand across all charger types. This period was therefore excluded from the Day Archetypes.

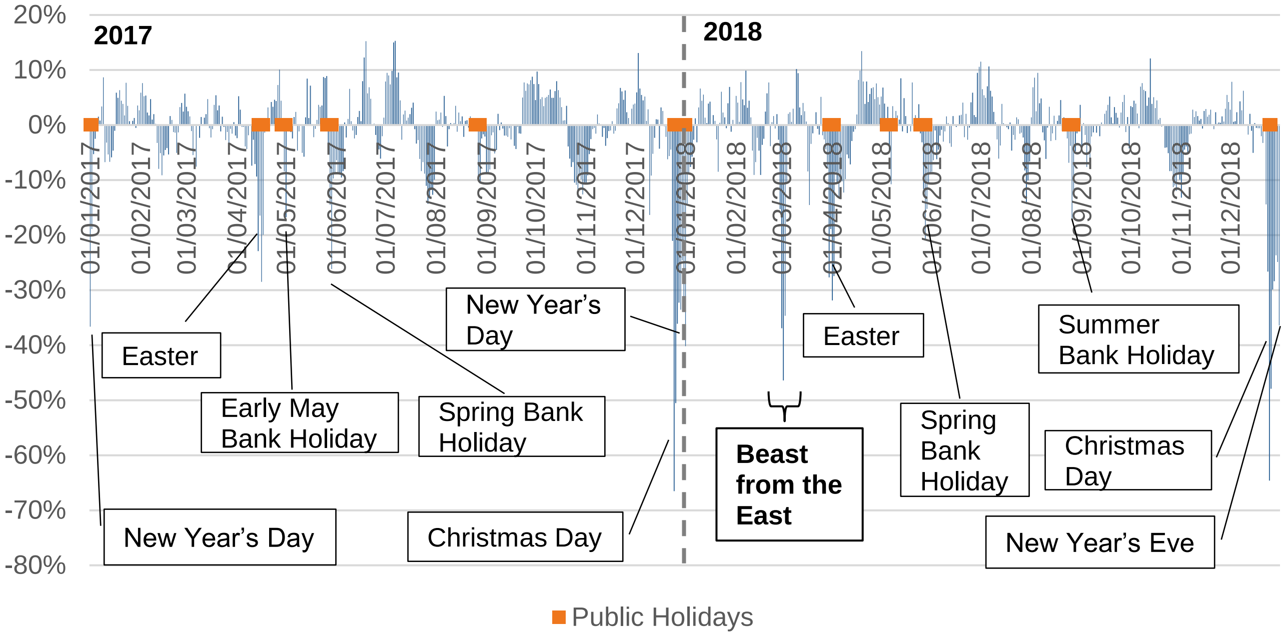

Figure 6-19: Variance to daily demand (kWh/day) of Day Archetype for residential charging.

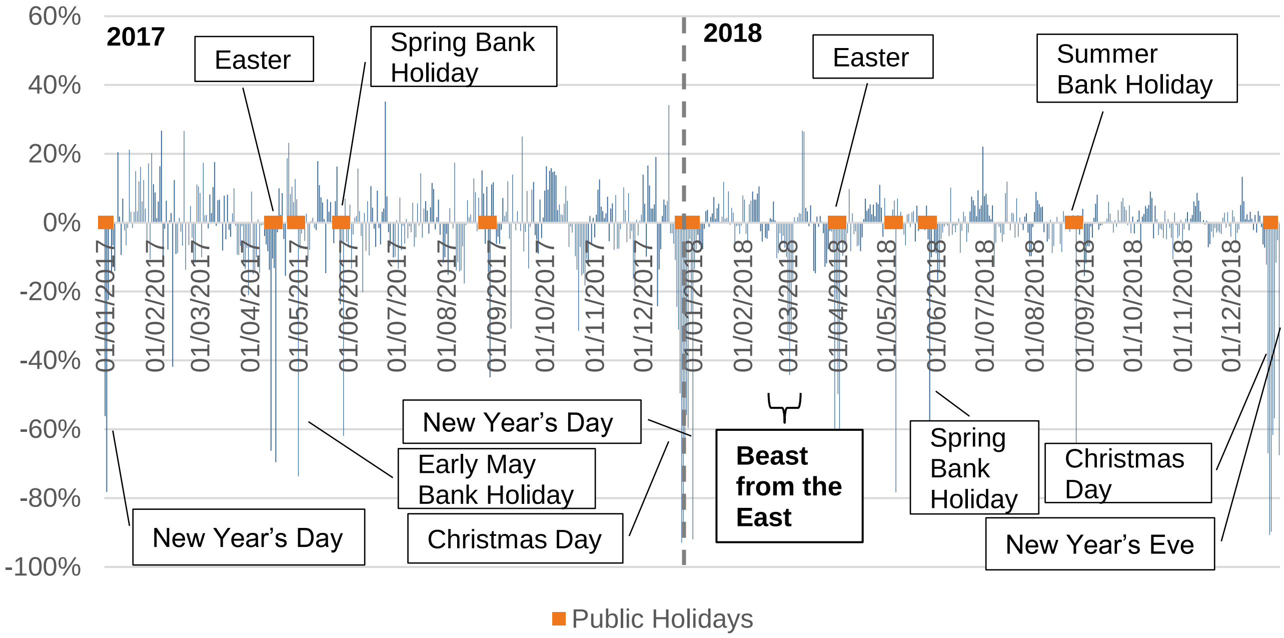

Figure 6-20: Variance to daily demand (kWh/day) of Day Archetype for work charging.

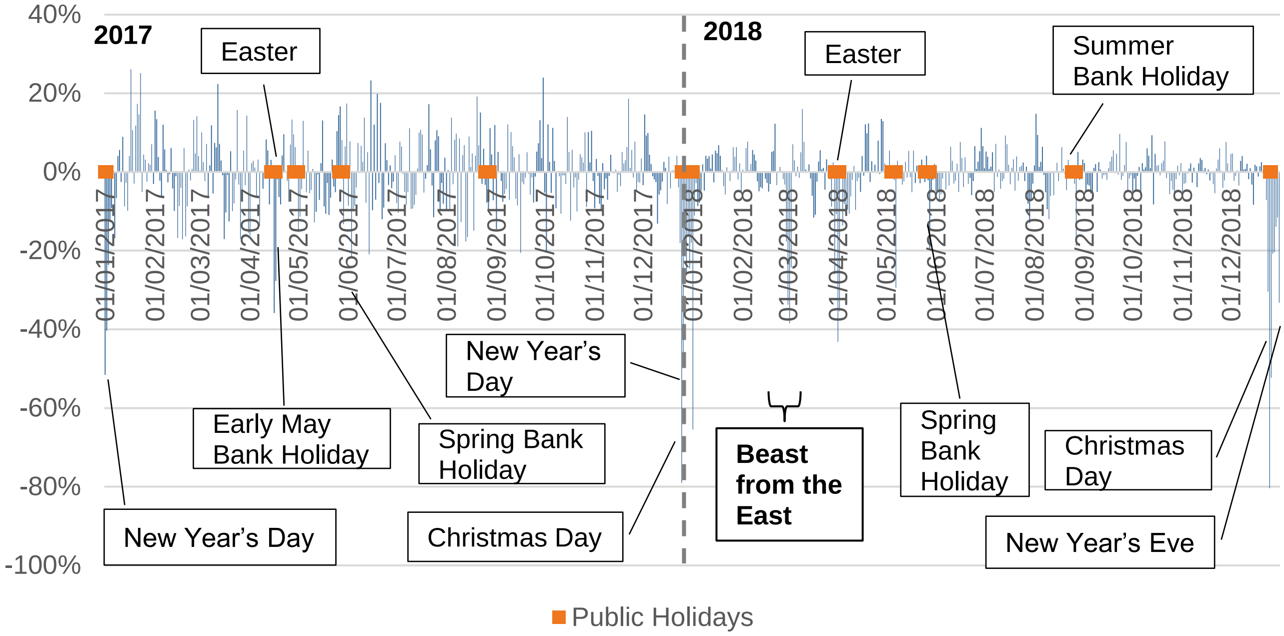

Figure 6-21: Variance to daily demand (kWh/day) of Day Archetype for slow/fast public charging.

6.4.6 Adding back in the effect of temperature

Daily demand profiles for a full year were created for each charger type by placing the daily demand from each Day Archetype in the required order. Since the effect of temperature was removed in the creation in the Day Archetypes, this is added back into the resultant daily demand profile, using the correlations shown in Appendix 6.4.2). For this, the average daily temperatures from 2017 were applied (see Figure 6-22), however, this approach also allows other temperature profile to be used for the purpose of, for example, system stress testing.

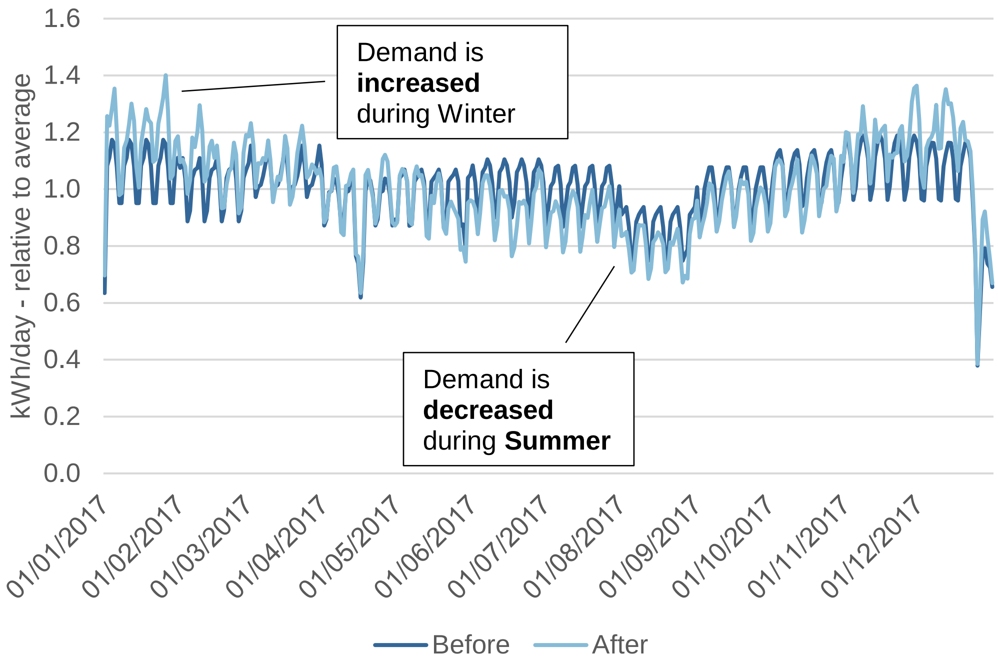

Figure 6-22: Example of re-adjustment of daily demand profile (residential) to add back in the effect of temperature.

6.4.7 Stitching together hourly demand from Day Archetypes to create full year profile

Finally, full year hourly demand profiles for each charger type were generated by stitching together the normalized hourly demand profiles of each date's Day Archetype, scaling by the daily demand. The resulting full year hourly demand profile was then normalized to 1 kWh/year. An illustration of this process is shown in Figure 6-23

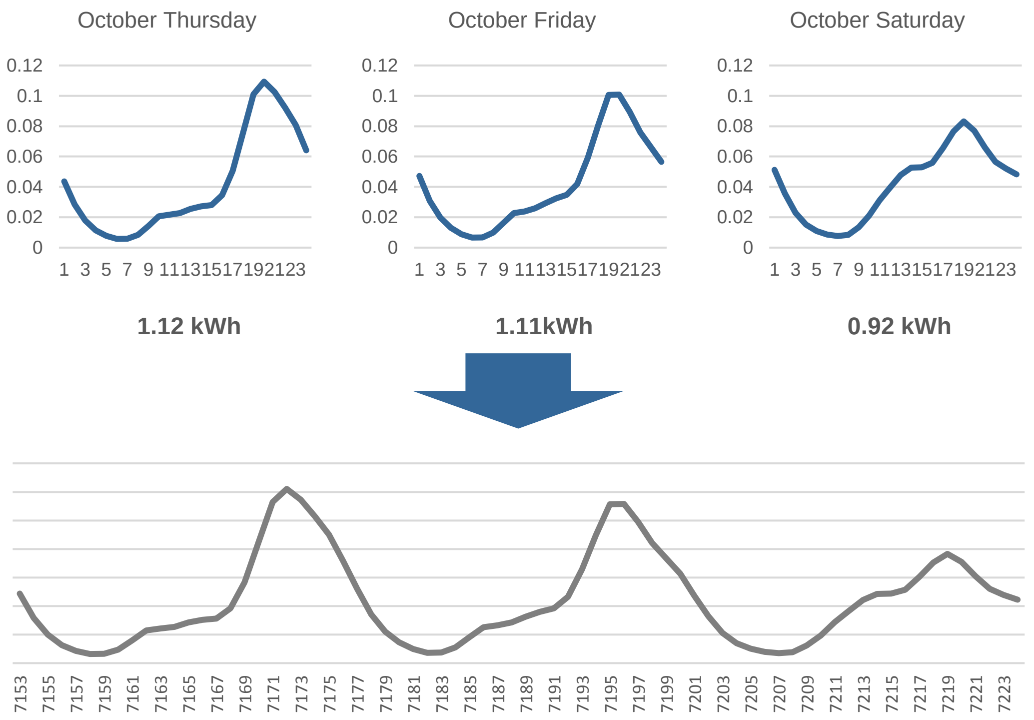

Figure 6-23: Example of how Day Archetype hourly demand profiles are scaled by daily demand and stitched together to create full year hourly demand profile.

6.5 Combining demand profiles from each charger type to generate overall GB-level charging profile

The normalized full year hourly demand profiles for each charger type were combined by first scaling by the estimated annual energy demand of that charger type. The assumptions behind these estimates are described in the following sections.

6.5.1 Estimating total kWh per year for an average EV

Element Energy's ECCo model employs a choice model to forecast sales of EVs in the GB, which are passed to a stock model which computes their usage over their lifetimes. This model is used by the Department for Transport to assist in EV policy design. ECCo can therefore be used to generate average (real world) energy consumption figures for BEVs and PHEVs in the current GB stock. These consumption figures were then translated to annual energy consumption assuming the current average annual mileage of 13,200 km[8]. The result is shown in Table 6-3, and provides a weighted average annual energy consumption of 1,760 kWh/year.

Table 6-3: Assumed current energy consumption of BEVs and PHEVs.

	Average kWh/km	Annual kWh	EV stock share (2018)
PHEV	0.10	1,350	67.5%
BEV	0.20	2,620	32.5%

[8] DfT Data Tables TRA0201 and DfT Data Table VEH0102

6.5.2 Estimating share of charging met by each charger type

There is limited data available on how different EVs distribute their charging across the different charger types. This requires a detailed monitoring of EVs where the charge point type used for each charge event is known. No dataset of this type and size required currently exists for GB. Consequently, findings from available data were used to inform estimates for these input parameters.

Slow/Fast Public

The Electric Nation survey[9] asked participants how often and for how long they charge at supermarkets, car parks and on street charge points. Assume that all of these charge points fall under our Slow/Fast Public definition, the average number of charges per day at these locations was 0.038 (there was little difference between PHEVs and BEVs).

The average energy per charge for Slow/Fast Public charging events in the database is 7.4 kWh. This gives the following central assumption for share of charging demand at Slow/Fast Public charge points:

Charges per day		kWh per charge		Annual kWh supplied	Total consumption kWh/yr (2018)	Share of total consumption
0.038	x	7.4	=	103	1,760	**5.8%**

Work

The Electric Nation survey[9] also asked participants who charge at work, how often they did so. The PHEV drivers plug-in more often at 0.61 times per day vs 0.39 times for BEVs

Work charge points are only used by commuters, who on average drive higher annual mileages than non-commuters. The share of cars used for commuting is 53%[10] and commuters have an annual mileage 77% higher than non-commuters[11]. Combined, this equates to average annual mileage of 16,600 km for commuters (relative to a national average of 13,200) and thus higher annual energy consumption than the average EV.

The average energy per charge for work charge events in the database is 9.2 kWh. For PHEVs, usable battery capacities are 4-8 kWh so they cannot accept all this charge. Electric Nation shows the average home charge for PHEVs is 6.0 kWh suggesting they do a full charge each time. It is likely that PHEV drivers will also charge at work when their battery is near empty i.e. 6.0 kWh/charge.

Accounting for the current ratio of BEVs to PHEVs, average energy per charge at work for BEVs is therefore estimated to be 16.0 kWh (to ensure an average charge event of 9.2 kWh)

The above assumptions can be used to estimate share of charging at work for commuter EVs:

[9] Data analyzed by Element Energy as part of UK Power Networks (2019) Recharge the Future.
[10] RAC Foundation (2013) The Car and the Commute.
[11] Element Energy analysis of National Travel Survey 2009.

	Charges per day		kWh per charge		Annual kWh supplied	Total consumption kWh/yr (2018)	Share of total consumption
BEVs	0.39	x	16.0	=	2,280	3,300	**69%**
PHEVs	0.61	x	6	=	1,340	1,700	**79%**

Note that these shares are for commuters who have access to a work place charge point. Not all work places will have charging available and so these represent sensible upper bounds. It was assumed that currently 30% of EV commuters have access to workplace charging, based on the Electric Nation sample. Therefore on average, 21% of BEV commuter demand and 24% of PHEV commuter demand was estimated to come from work charging.

Accounting for the commuter share (53%), BEV/PHEV ratio, and higher commuter energy demand, this means 14.7% of total EV charging demand was estimated to be met by work charging.

Rapid Public

It is assumed that PHEVs do not use rapid charge points, as their batteries are too small and only the Mitsubishi Outlander is compatible with DC rapid charging. However, even this model is unable to charge at rapid charging speeds and charge point operators actively discourage it from using their networks because it depresses utilisation.

The My Electric Avenue trial found that rapid charging accounted for 9.2% of total charging demand[9]. However, this trial was limited to 24 kWh Nissan Leafs only, which charge at <50kW due to their small battery size. EVs with larger batteries will be able to charge at a higher rate, but may have less need for rapid charging due to their longer ranges. Since these effects will cancel one another out to some extent, it is therefore suggested that rapid charging accounts for 10% of total kWh consumption for BEVs.

BEVs account for only 32.5% of the current EV stock but have higher energy demand than PHEVs. Thus, rapid public charging was estimated to contribute 4.8% of total charging demand.

Residential

Charging demand at Residential is assumed to be the total demand minus the charging demand at the other three locations. Thus, 75% of charging demand was estimated to come from residential charging.

Table 6-4: Assumed share of charging and annual consumption per EV at each charger type.

	Average Annual kWh			EV share of kWh
	BEV	PHEV	EV	
Residential	1860	1050	1310	**74.6%**
Work	360	210	260	**14.7%**
Slow/Fast Public	140	80	100	**5.8%**
Rapid Public	260	0	90	**4.8%**

Table 6-4 shows the resulting shares and annual charging demand per EV met by each charger type. Note that for Residential charging data collected for this work, the average kWh per year per charge point is 1940 kWh. This is clearly higher than the 1,310 kWh estimated for an average EV. However, the sample includes only EV drivers that have a home charge point installed (approximately 50% of EV owners[3]). These are more likely to be BEV drivers who do not have access to work charging, and thus would be expected to carry out a larger share of charging at home than an average EV.

6.6 Profile Diversity Analysis

An analysis has been conducted to investigate how the number of charge events per day effects demand profile diversity.

For each charger type, demand profiles were generated for a range different sub-samples of charge events. Each sub-sample profile (x) was compared with the fully diversified demand profile from the full sample (y), via the correlation coefficient:

$$corr(x,y) = \frac{cov(x,y)}{\sigma_x \sigma_y}$$

Figure 6-24 illustrates how the correlation coefficient increases with increasing sample of charge events, for residential charging.

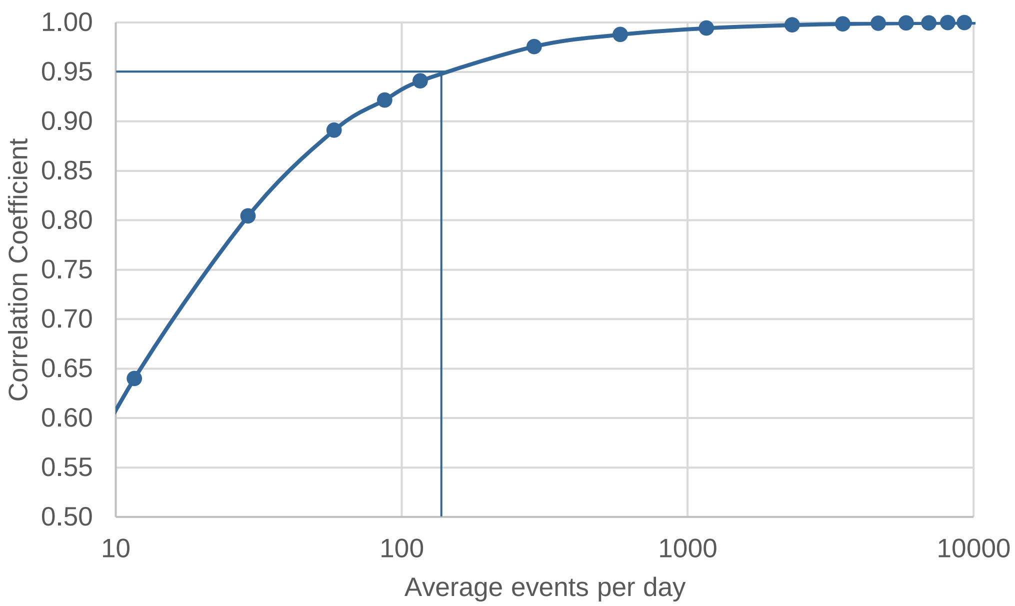

Figure 6-24: Correlation coefficient between full sample and sub-samples of increasing size (average events per day), for residential charging.

A sub-sample profile was considered diversified if its correlation coefficient was ≥0.95. For residential charging this is when the sub-sample has an average of >162 charge events per day. For the other charging locations, this threshold was found to be:

- Work: 73 events per day
- Slow/Fast Public: 176 events per day