NIC Project UKPNEN03 Deliverable D7

Appendix 2
Findings from the Optimise Prime Trials

February 2023

Optimise Prime

HITACHI Inspire the Next · Uber · Scottish & Southern Electricity Networks · centrica · Royal Mail · UK Power Networks

Contents

Insights gained from the trials

This appendix presents the key insights gained from the data gathered in the Optimise Prime trials. It is split by workstream and covers findings from the operational analysis of the fleets, load profile analysis and network impacts. While this appendix focuses on the observed and predicted impact of fleets on the network, Appendix 1 details insights from the trial of the Optimise Prime Methods, including flexibility services and profiled connections.

1 WS1 – At-home charging trial

The home trials collected data from vehicles and chargers in order to analyse the charging patterns of home-based commercial vehicles.

1.1 Data collected

The project released a number of datasets in Deliverable D6 that represent the primary data collected as part of the trials. These include:

Table 1 – Data collected in WS1

Dataset	Source	Data
EV Charging Data	Centrica charge point management system	Charging event data by CP, including start time, end time, charging and plug-in duration and kWh delivered in each charging event.
Trip Data	EV telematics systems	The start and end time and location of each trip made by each EV, together with the distance travelled in miles.

In addition to this, the trials made use of a number of additional data sources. Centrica also used more detailed data on the performance of flexibility events in order to create the analysis included in Appendix 1.

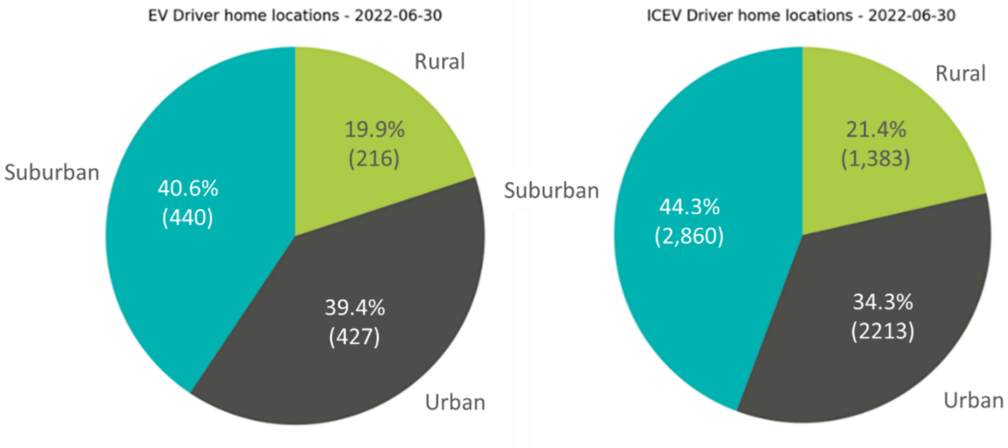
1.2 Operational analysis

Based on the telematics data collected from each vehicle, the project has analysed the locations and distances travelled of the EV fleet in order to compare this with the ICEV fleet. This analysis allows the project to judge how closely the EV sample resembles the rest of the British Gas fleet and how relevant the findings will be when scaled to the whole fleet.

1.2.1 Locations of drivers in the trials

The British Gas drivers involved in the trial were located throughout Great Britain. Figure 1 shows the breakdown of the EV drivers (left chart) across three location types, rural, suburban and urban. This can be compared with British Gas' ICEV vehicle fleet (right chart). As can be seen, the split of the fleet differs slightly, with a marginally greater proportion of EVs in the urban area, but the difference between the two groups is very minor. The methodology for defining area types has been updated since the previous analysis in Deliverable D4, utilising the Rural Urban Classification Methodology of the Office of National Statistics[1] and National Records of Scotland[2]. Figure 2 and Figure 3 shows the location of driver homes by local authority area.

Figure 1 – British Gas driver locations as of 30 June 2022 (EV left, ICEV right)



[1] 2011 rural/urban classification - Office for National Statistics (ons.gov.uk)
[2] https://www.gov.scot/publications/scottish-government-urban-rural-classification-2020/pages/3/

Figure 2 – EV driver home location by local authority area

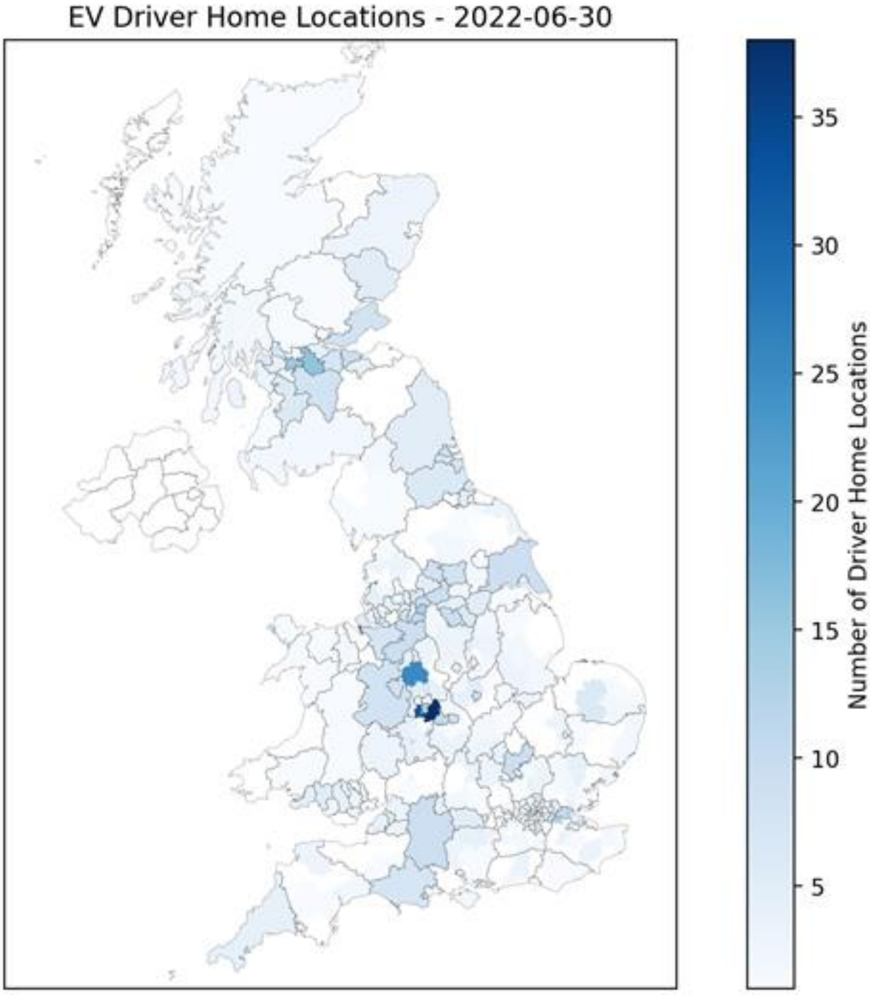
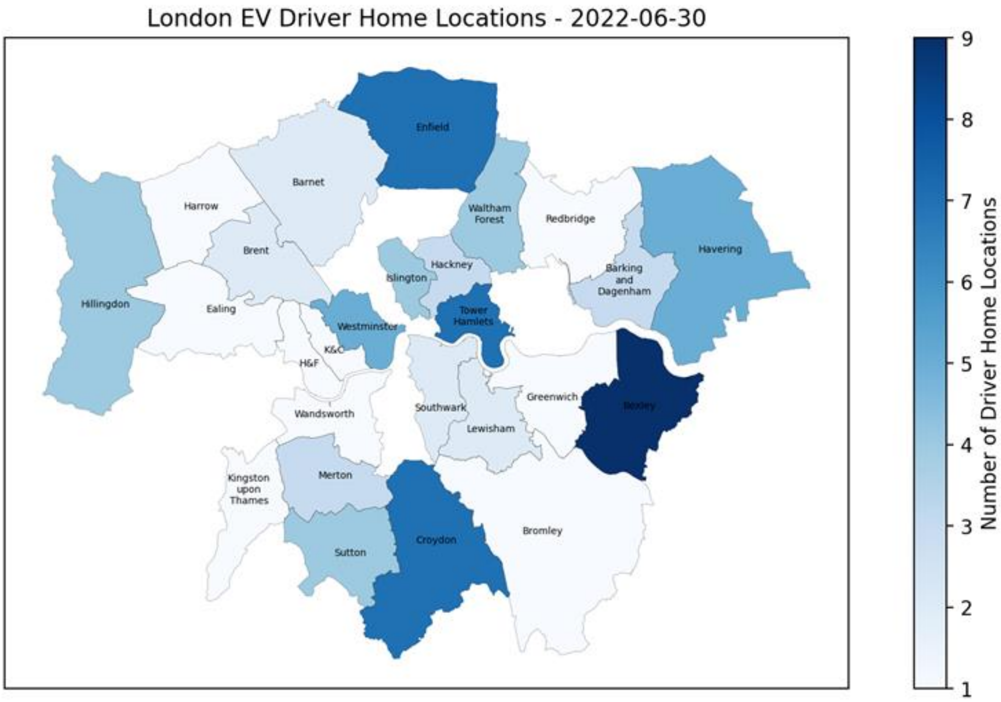


Figure 3 – EV driver home locations by London Borough



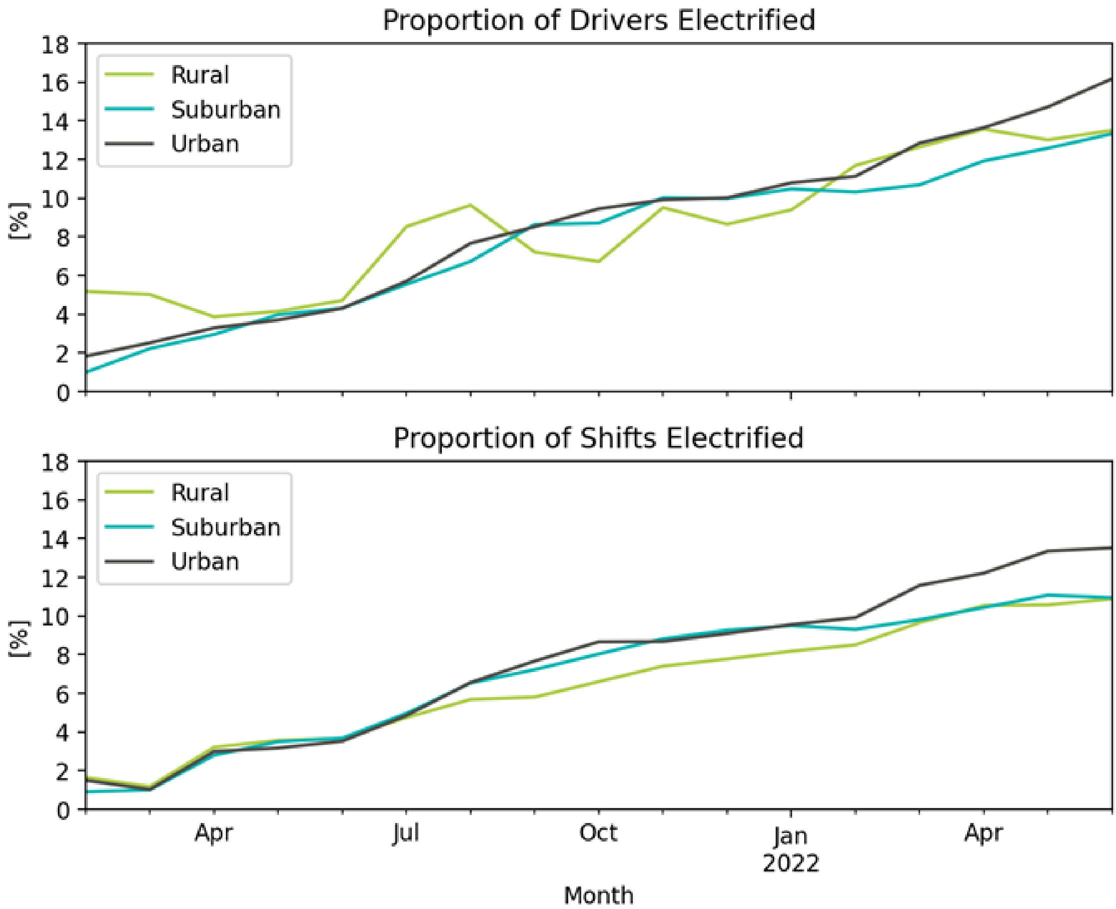
1.2.2 EV uptake over time, by location type

Drivers from each home location category show a similar rate of electrification over time, as shown in Figure 4.

The rural location started with the largest proportion of EV drivers, at 5% of the national fleet, which has increased to 13.5% by June 2022.

Urban electrification has been the fastest growing driver home location type, increasing from 1.8% to 16.2% over the period analysed.

Figure 4 – EV Uptake over time by location type

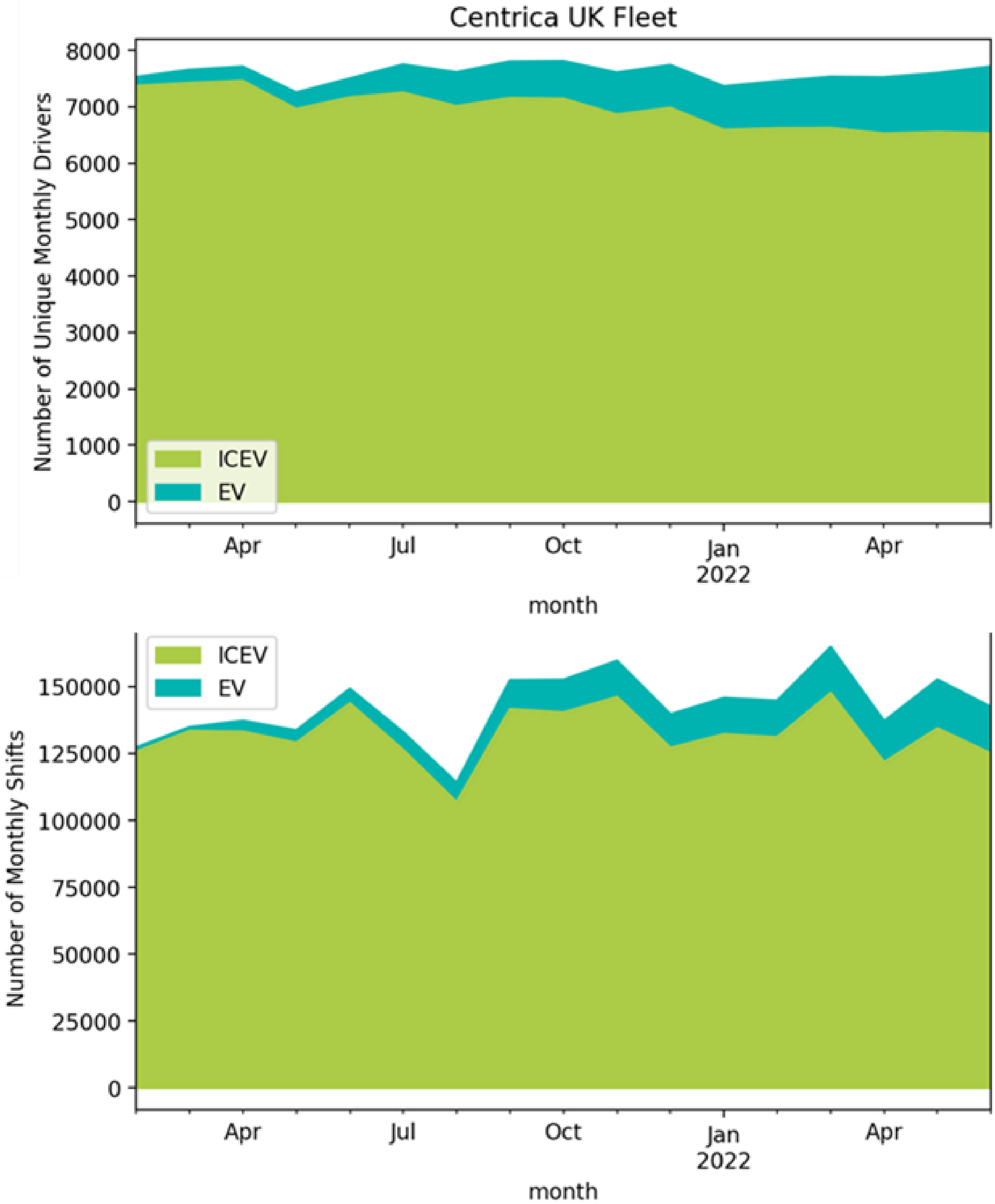


1.2.3 Driver shift analysis

1.2.3.1 Changes over the course of the trials

Over the course of the Optimise Prime trials, the number of EVs in the British Gas fleet has increased – from 106 in February 2021 to 1,135 at the end of June 2022, as shown in Figure 5. There has been a corresponding decrease in the number of ICEV drivers, keeping the total number of vehicles in the fleet roughly constant. Figure 5 also shows the number of shifts undertaken by each vehicle type. This changes in line with the proportion of EVs. However, it is also impacted by seasonal patterns of demand for British Gas services, and drivers taking leave. This will be discussed further later in this section.

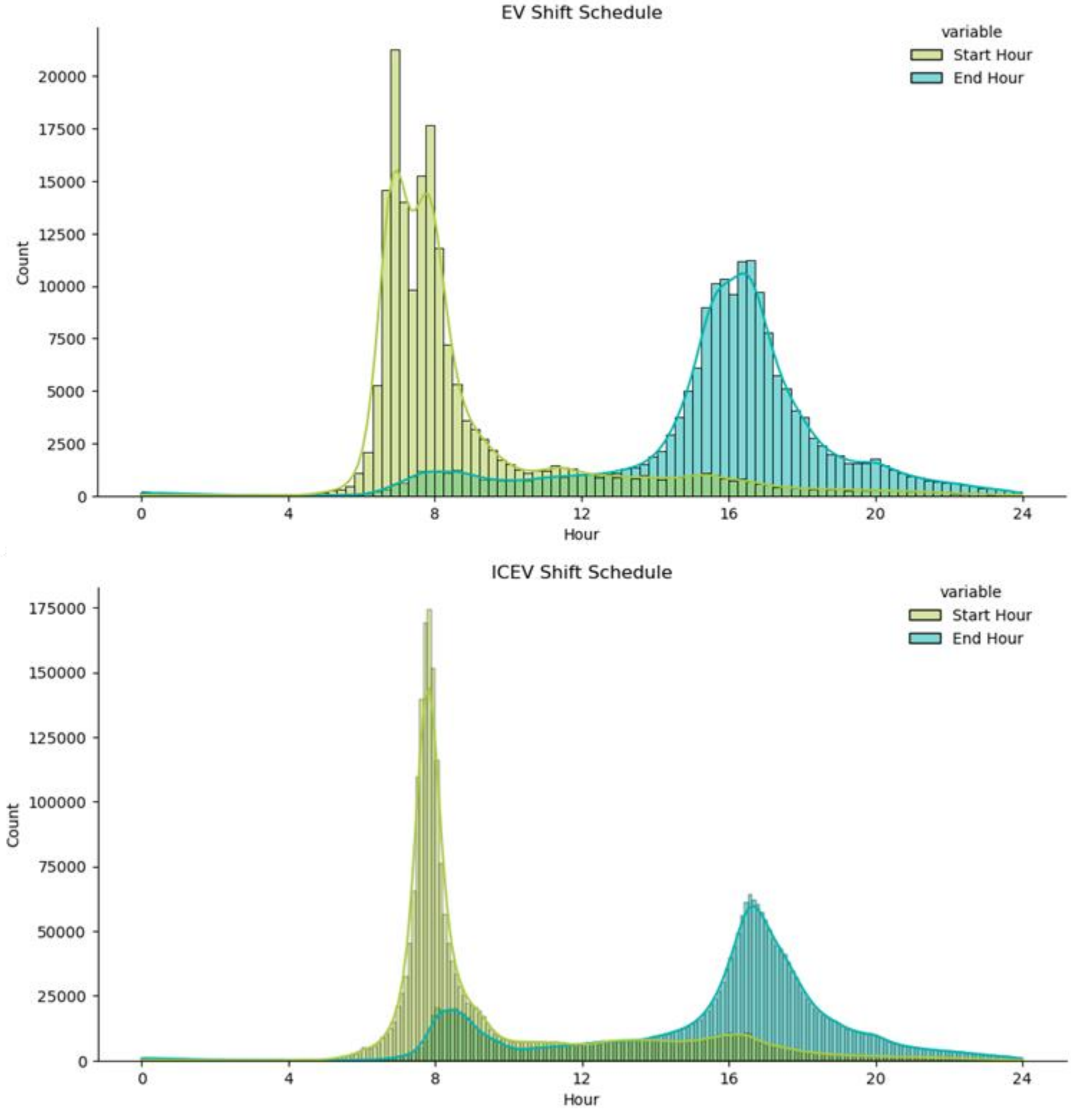
Figure 5 – Changes in EV and ICE driver and shift patterns over time



1.2.3.2 *Shift behaviour*

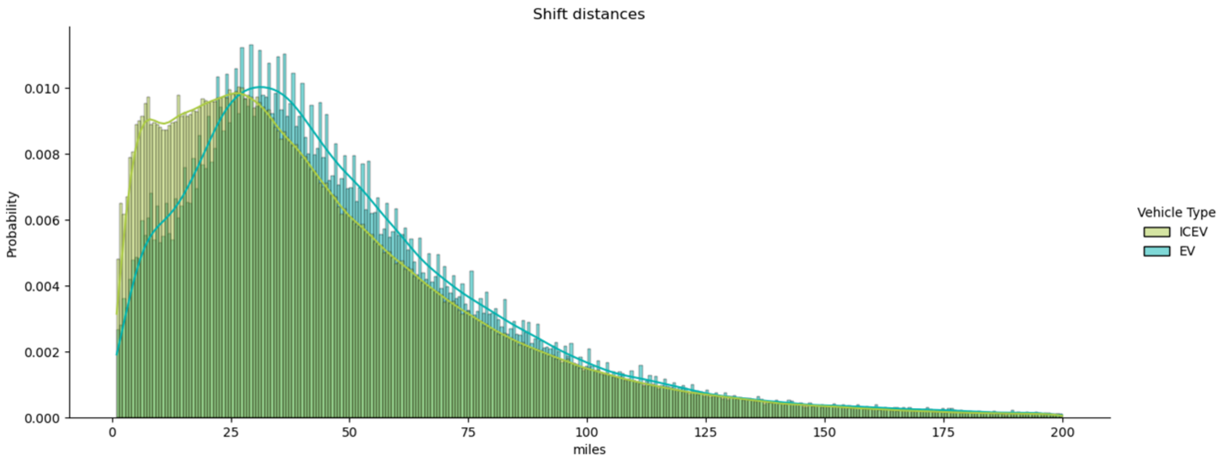
The average start and end time of shifts for EV and ICEV drivers is shown in Figure 6. The departure and return times of EV drivers are more spread out compared to ICE drivers, but the general pattern of timings is similar.

Figure 6 – Start and end times of EV and ICEV shifts



In terms of distances travelled, the EVs travelled slightly further than ICEVs, on average, with the majority of very short shifts being completed by ICEVs, as shown in Figure 7.

Figure 7 – Distance travelled on EV and ICEV shifts



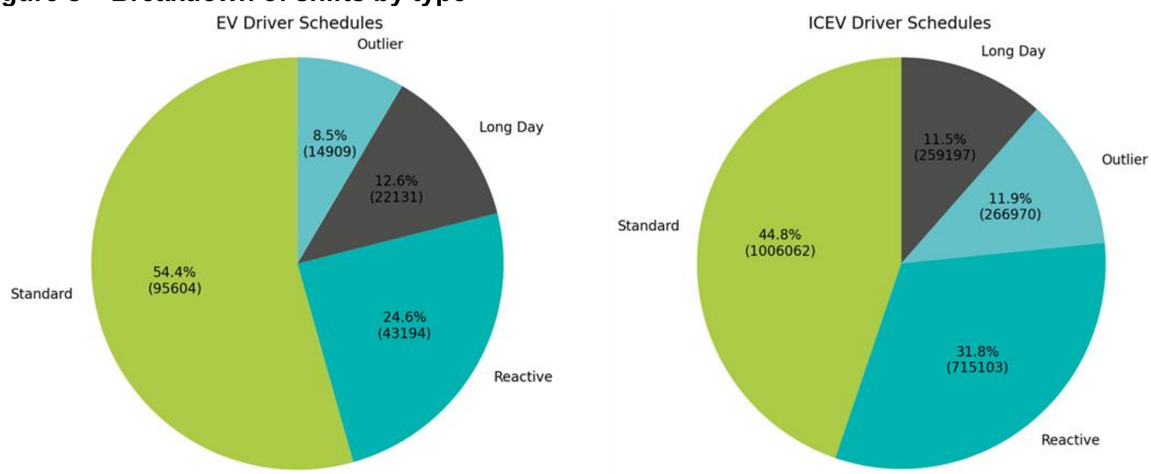
1.2.3.3 Shift types

To analyse the impact of shift patterns on load further, shift types were broken down into four categories, based on the following rules:

- **Standard** shifts start 06:40-13:20 AND end 13:20-20:00
- **Reactive** shifts do not follow the timing of a standard shift
- **Long Day** shifts have a duration of greater than 10 hours
- **Outliers** have a shift duration of greater than 15 hours OR less than 15 minutes.

Figure 8 shows the breakdown of shift types by vehicle technology. While the EVs generally follow the pattern of ICEVs, there are differences: EVs perform fewer reactive trips, which may be related to the longer charging periods making them more suitable for regular daily trip patterns. However, it is also notable that the EVs perform a greater proportion of long day shifts, showing they are capable of these more demanding schedules; indeed EVs are used to perform CP installation work on behalf of customers. While there are minor variations, the breakdown of shift type does not materially differ across urban, suburban and rural locations.

Figure 8 – Breakdown of shifts by type



1.2.3.4 Shift timings

Analysis of the ICEV schedules, shown in Figure 9, demonstrates that most shifts start in a concentrated period around 08:00, although some reactive shifts start throughout the afternoon.
Most reactive shifts end before 10:00, followed by standard shifts finishing at 17:00, and long day shifts at 18:30

The EV schedule, presented in Figure 10 shows that EV shifts are similar to ICEVs. A slightly wider distribution of start times can be seen, although this may be due to the difference in sample size.

Figure 9 – ICEV shift start and end times

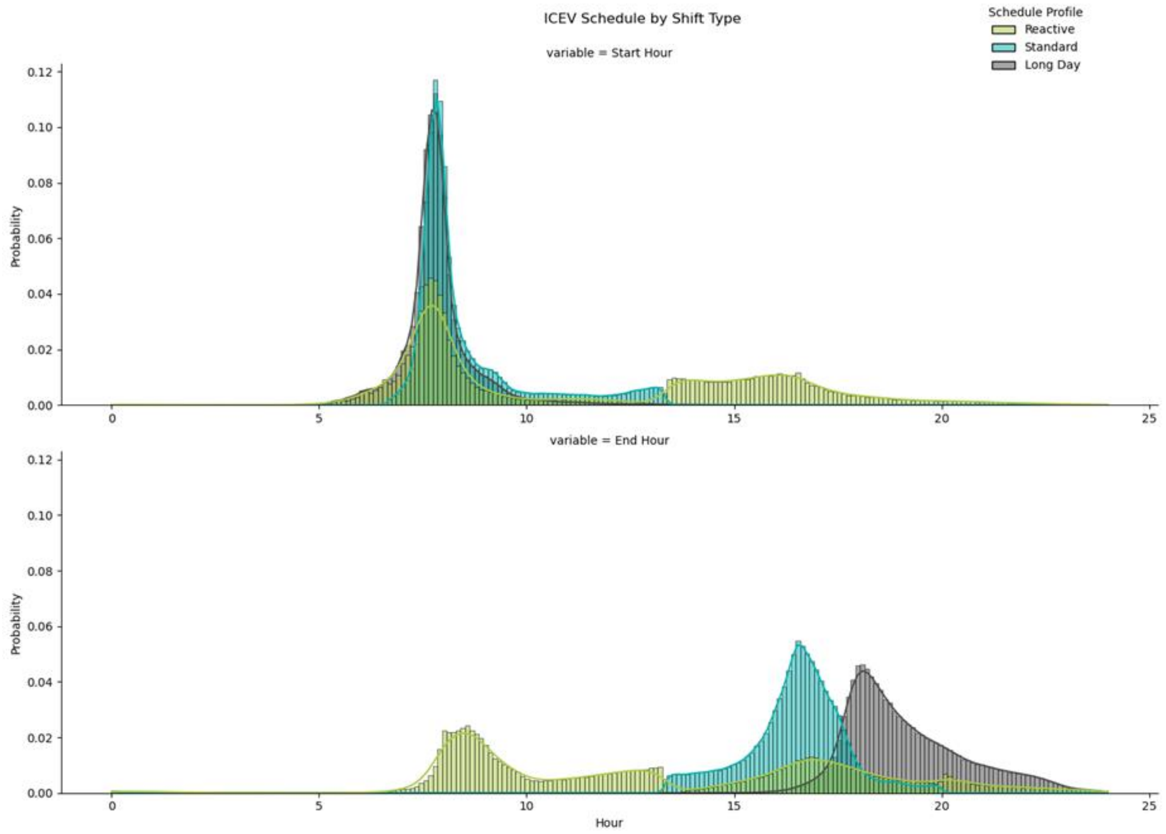
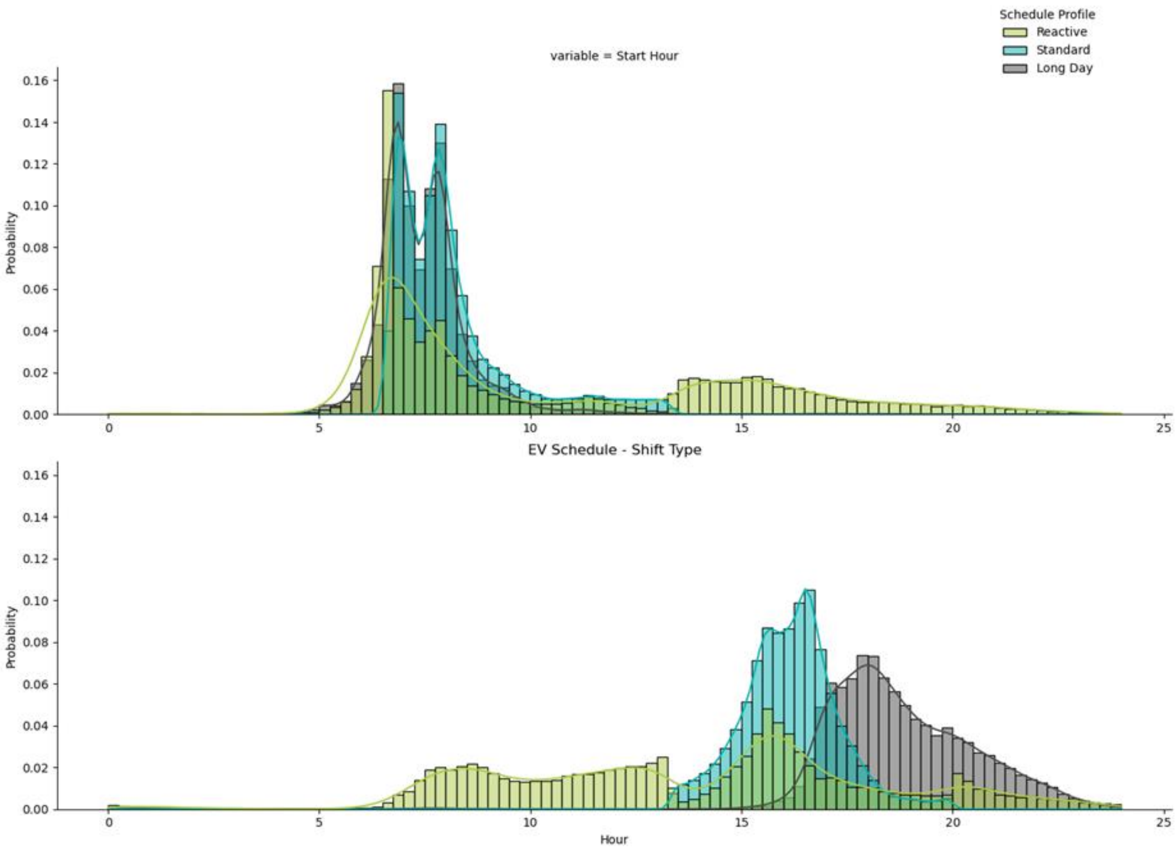


Figure 10 – EV shift start and end times



1.2.3.5 Shift distances

Shift distances were analysed across the vehicle and location types, as shown in Figure 11. Overall, EVs were found to do slightly longer distance shifts (~5-6 miles) compared to ICEVs across the home location types. This reflects the fact that EVs were less likely to do reactive shifts and more likely to undertake long days. Yet, as shown in Table 2 the length of each type of shift was also slightly longer for EVs.

Drivers living in urban areas have notably lower average shift distances compared to suburban and rural areas. As shown in Table 3, a rural EV driver travels 60% further than an urban EV driver on average.

Figure 11 – Shift distances by vehicle and location type

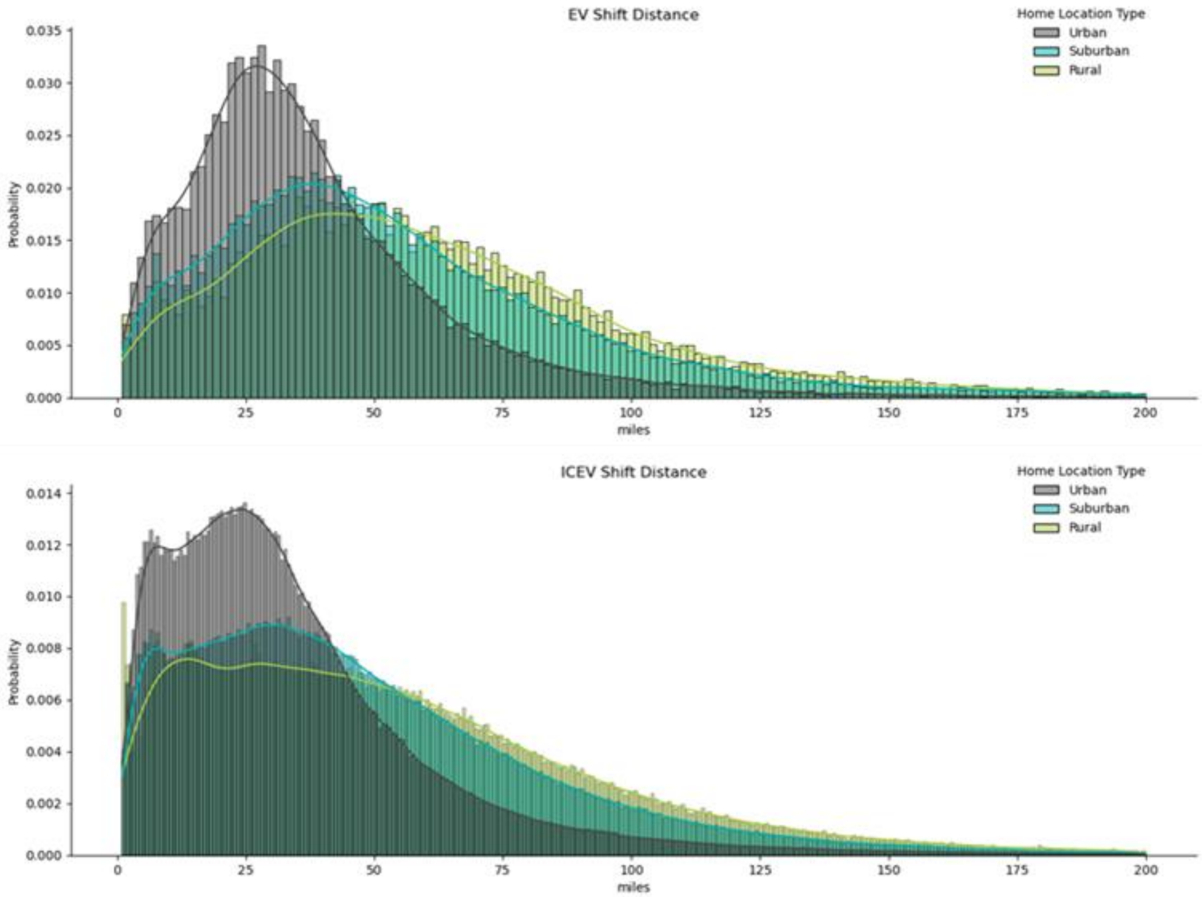


Table 2 – Mean Shift distances by vehicle and shift type (miles)

Vehicle Type	Standard	Reactive	Long Day
EV	51.3	33.8	69.6
ICEV	50.7	26.5	68.4

Table 3 – Mean shift distances by vehicle and location type (miles)

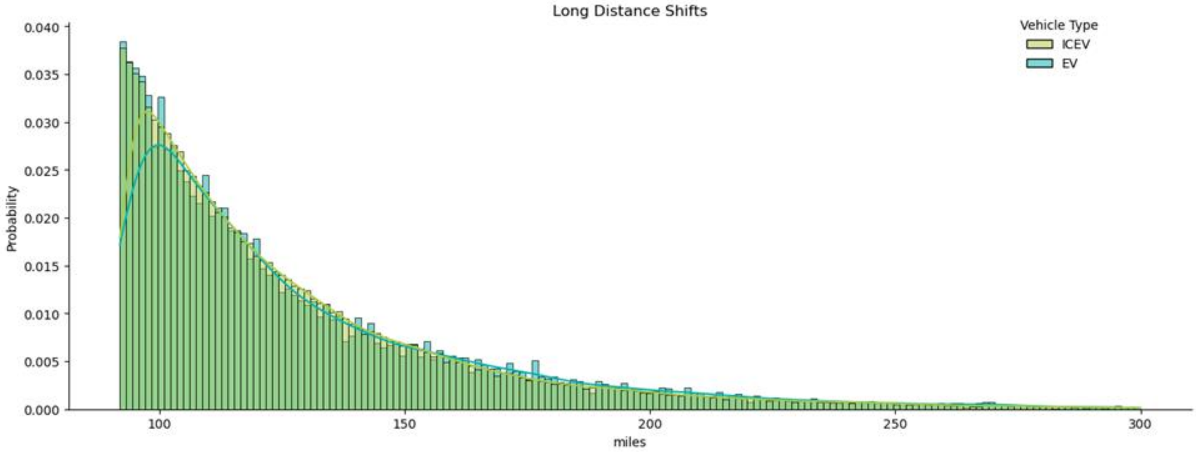
Vehicle Type	Urban	Suburban	Rural
EV	38.2	54.2	61.1
ICEV	34.6	48.1	54.0

1.2.3.6 Ability of EVs to complete longer schedules

A key barrier to EV adoption can be range anxiety – the fear that the EV is not capable of carrying out specific tasks due to the limitations of battery capacity. This was identified as a common concern among both non-EV and EV drivers in the behavioural research. However, analysis of long-distance shifts, defined as any shift which falls within the top 10% of shift distances, reveals that both EVs and ICEVs are able to cover similar distances, as shown in Figure 12.

Some of the longer ICEV journeys, in the distribution, are likely the responsibility of Centrica's business solution group which has an all-diesel fleet which regularly drives 250-300 miles/day.

Figure 12 – Distribution of shift distances by vehicle type



1.2.3.7 *Seasonal and daily variations*

Operations at British Gas have been found to vary seasonally. Figure 13 shows that shifts in the autumn and winter periods involve drivers travelling further than in the spring and summer. For EVs this difference in seasonal shift length was found to be greater than for ICEVs, though it is not clear what is causing this pattern. EVs travel approximately 10 miles further in the autumn and winter than in spring and summer on average, with the maximum journey length varying by up to 20 miles. Figure 14 shows the distribution of shift distances in each season – the EVs in particular can be seen to fulfil longer shifts in the winter.

Figure 13 – Seasonal variation in shift distances

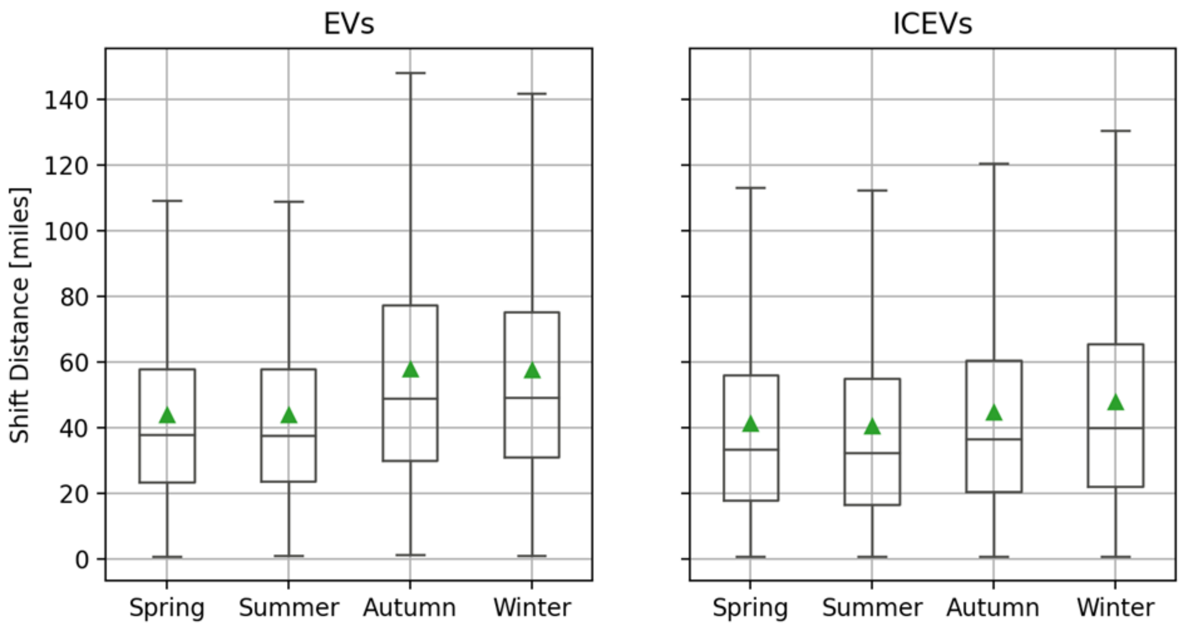
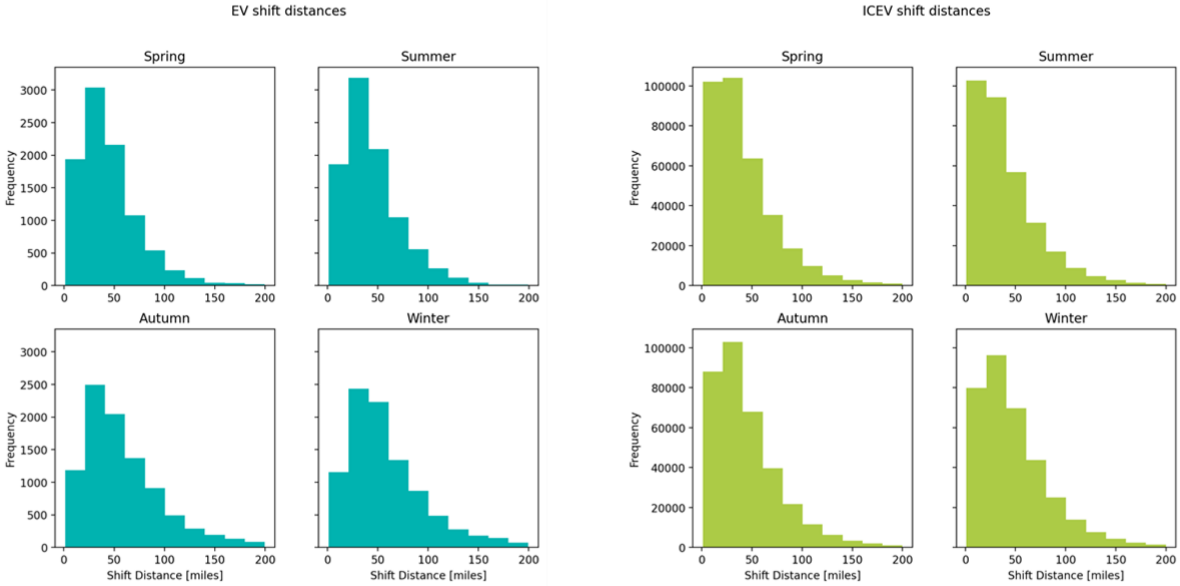
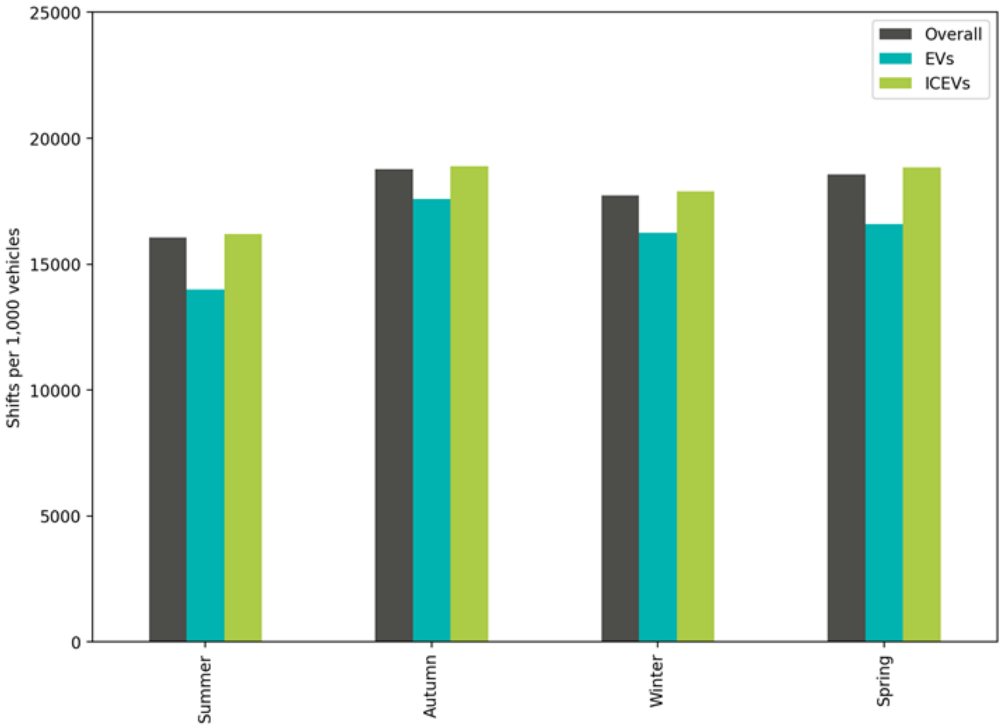


Figure 14 – Distribution of shift distances by season



In addition to the length of shifts varying by season, the number of shifts completed by each vehicle also varies, as shown in Figure 15. Summer has the lowest number of shifts, because of holidays taken and less use of heating, while the Autumn Switch-On is British Gas' busiest period when customers typically turn on boilers that have not been used since Spring. This is seen clearly in the data.

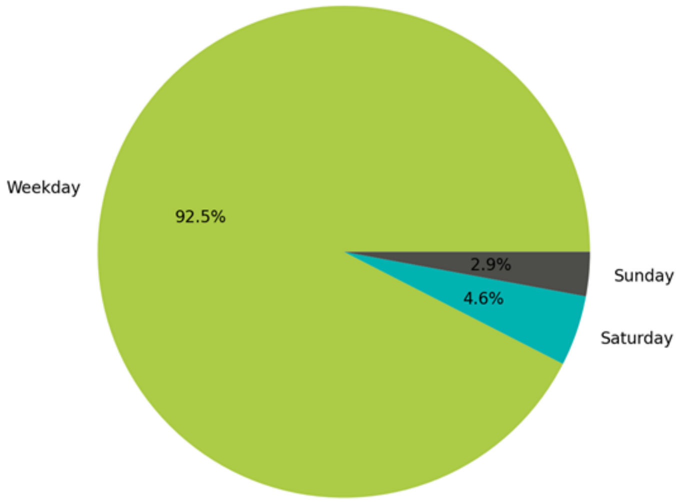
Figure 15 – Shift volumes by season



Summer (June 21' – August 21'); Autumn (September 21' – November 21'); Winter (December 21' – February 22'); Spring (March 22' – May 22').

Assessing patterns within the week, over 90% of shifts occur between Monday and Friday, as shown in Figure 16, with less than 3% of shifts occurring on Sundays.

Figure 16 – Proportion of shifts occurring on weekdays versus weekends



However, Sunday has longest average shift distance. This could be explained by the smaller number of available drivers having to drive further on average to reach customers for emergency call outs. Drivers also travel slightly further on Saturdays compared to weekdays, as shown in Table 4.

Table 4 – Mean shift distance (miles) by day and shift type

	Standard	Reactive	Long Day	Overall
Weekday	50.6	26.7	67.9	44.6
Saturday	51.6	22.5	76.1	42.7
Sunday	56.7	38.5	84.5	49.2

1.2.3.8 Changes over the duration of the trials

The number of EVs in the fleet increased significantly during the period of the trial. To show the seasonal variation without the impact of the higher numbers of EVs, the changing shift pattern of the vehicles that were present in February 2021 was studied. Figure 17 shows the pattern throughout the year, with a demand peak in the autumn and lower demand in the August and December/January holiday periods. Figure 18 shows a relatively stable average mileage, with some peaks occurring in the winter period. The patterns observed from these initial vehicles broadly aligns with those in the fleet, as a whole, although the increase in length of trips in winter was at the higher end of the distribution.

Figure 17 – Seasonal variation in shift patterns of February 2021 EVs

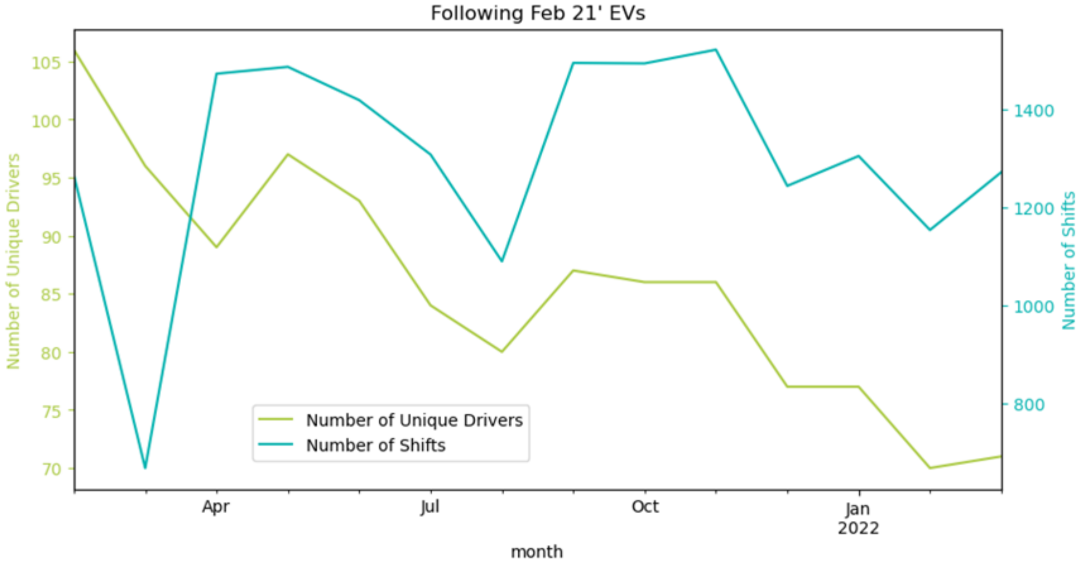
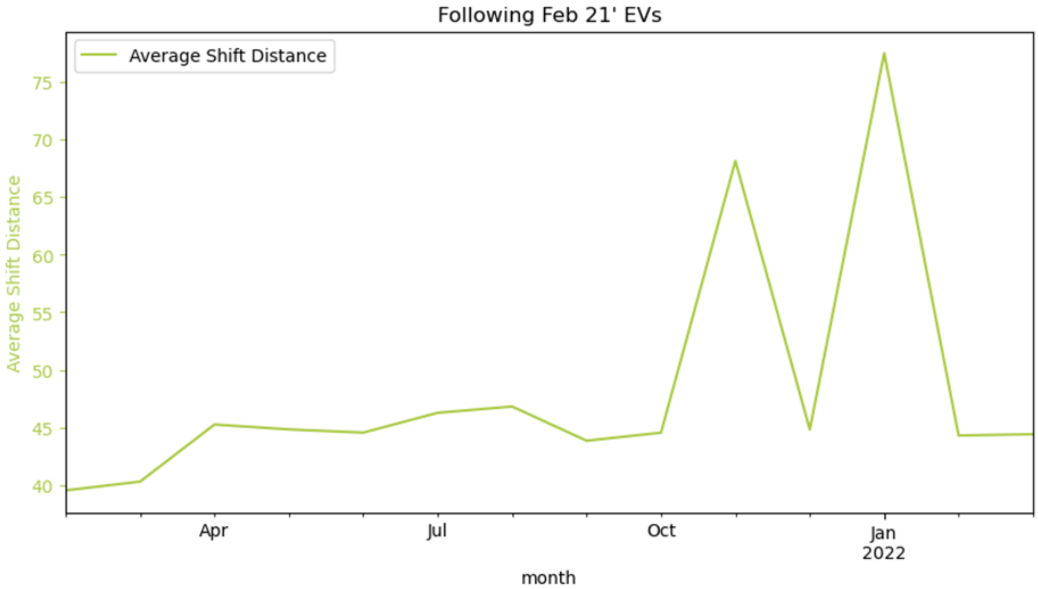


Figure 18 – Seasonal variation in trip length of February 2021 EVs

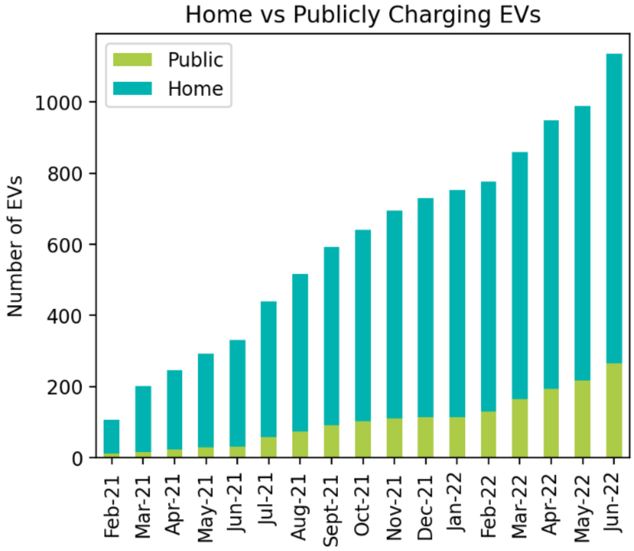


1.2.4 Public charging of British Gas EVs

At the outset of the project, it was presumed that the home-based British Gas vehicles would principally be charging at home. As the EV rollout progressed, it became clear that a significant proportion of drivers would have to make use of public charging due to lack of off-street parking or inability to install charge points because of physical or electrical constraints at the driver's property.

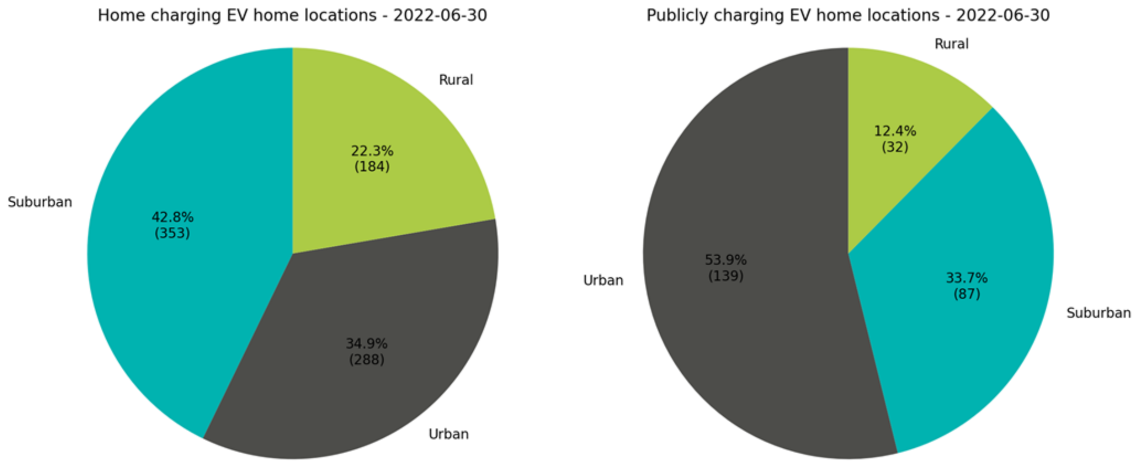
Figure 19 shows the proportion of drivers that make use of public charging vs drivers who rely solely on home charging. The proportion making use of public charging has steadily increased from 10.4% in February 2021 to 23.3% in June 2022 and is expected by Centrica to increase to 60%, by 2030, when all vehicles are electrified.

Figure 19 – Use of Public vs. Home charging by British Gas drivers



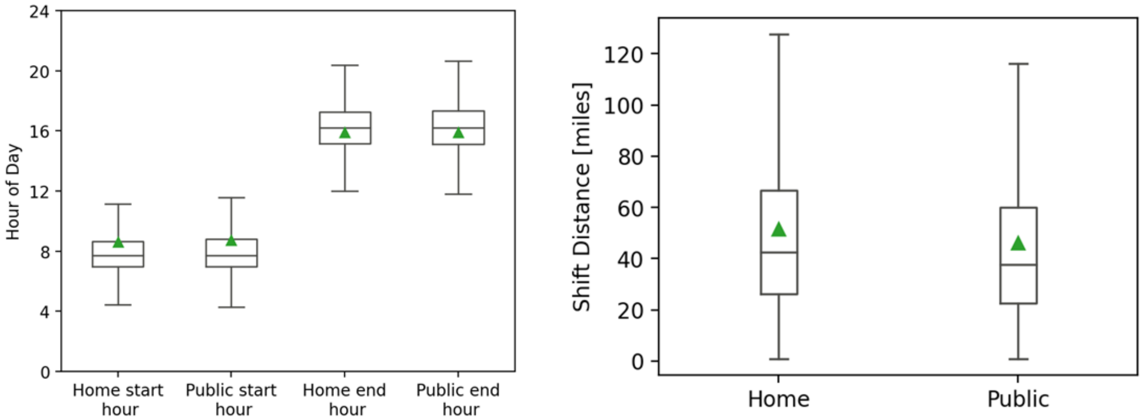
The drivers that make use of public charging are much more likely to be based in an urban location compared to drivers that charge at home, as shown in Figure 20.

Figure 20 – Location of drivers that use only home charging vs users of public charging



Shift distance and the start and end times of shifts were similar for public and home charging, as shown in Figure 21, suggesting that public charging had limited effect on the working routine of drivers. The breakdown of shift type across home and public charging drivers was also very similar.

Figure 21 – Comparison of shift timings and distances for users of home and public charging



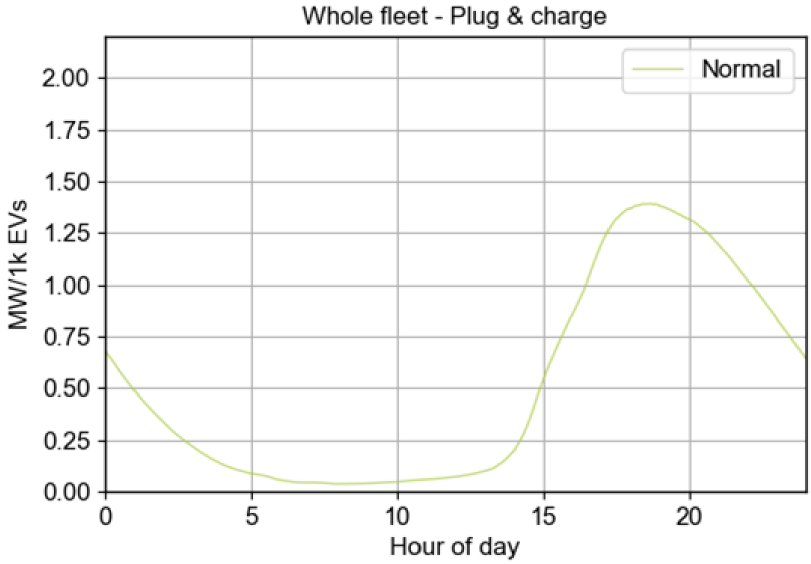
1.3 Load profile analysis

Load profile analysis looks at the actual demand measured from the CPs in the trial in order to show where peaks occur in charging demand. Several scenarios, including unmanaged, smart and flexible load profiles, are considered. Because of the limited charging at weekends, this analysis focuses on weekday behaviours unless otherwise indicated.

1.3.1 Load Analysis for unmanaged charging

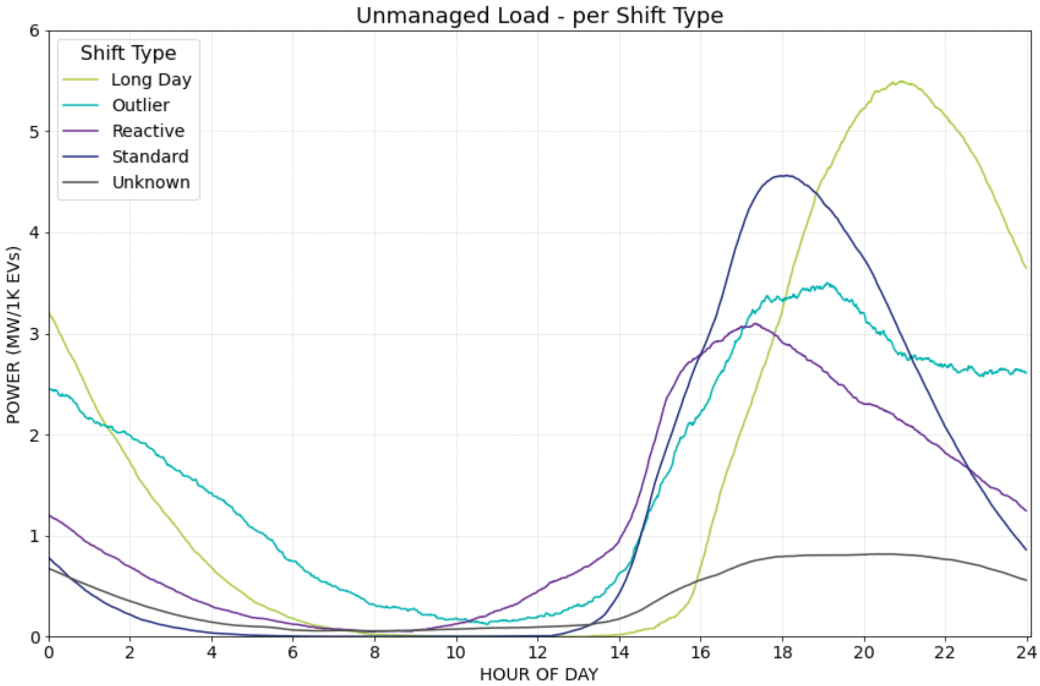
The British Gas fleet generally charges in an unmanaged way, where drivers plug in their EV once they return home and the vehicle charges until the battery is full. Figure 22 shows how the average load from the British Gas EVs on a typical weekday, scaled to 1,000 vehicles. Vehicles plug in gradually between 14:00 and 18:00, resulting in a peak in demand that falls at around 19:00. The maximum load is around 1.4MW per 1,000 EVs, reflecting that not all EVs will be actively charging simultaneously.

Figure 22 – British Gas unmanaged fleet charging load per 1000 EVs



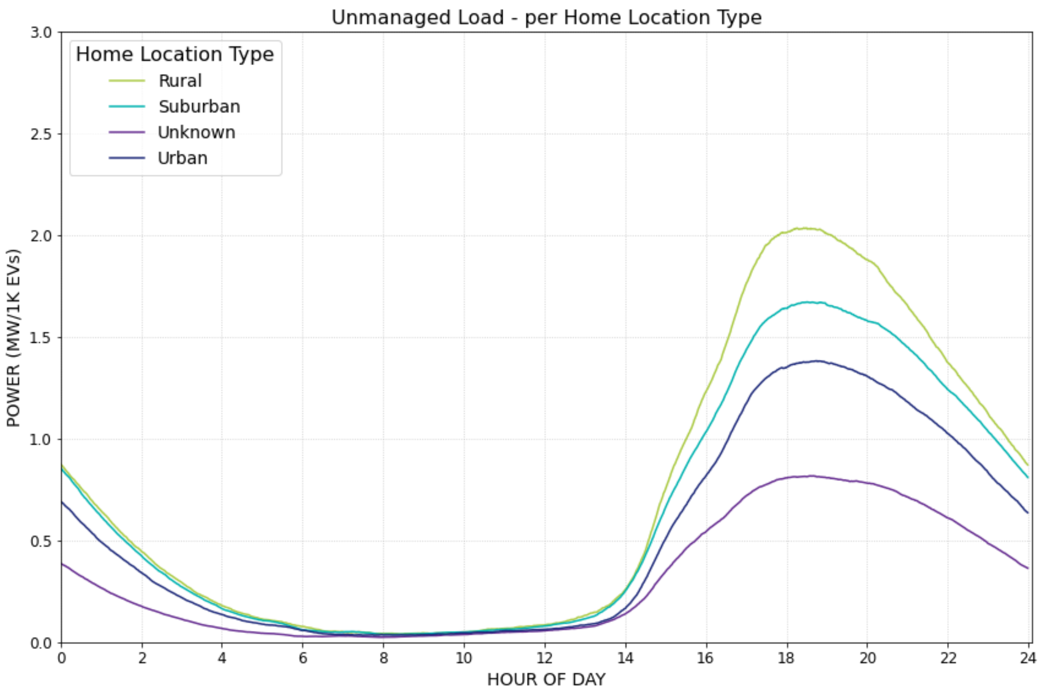
Breaking this down into the shift types, explored in the operational analysis (Figure 23), the type of shift has a bearing on both the time and magnitude of load on the network. As would be expected, the long day shift has a higher and later peak, while the outlier/reactive shifts have lower and less concentrated peaks, reflecting their lower mileages and varying shift times.

Figure 23 – Charging load by shift type



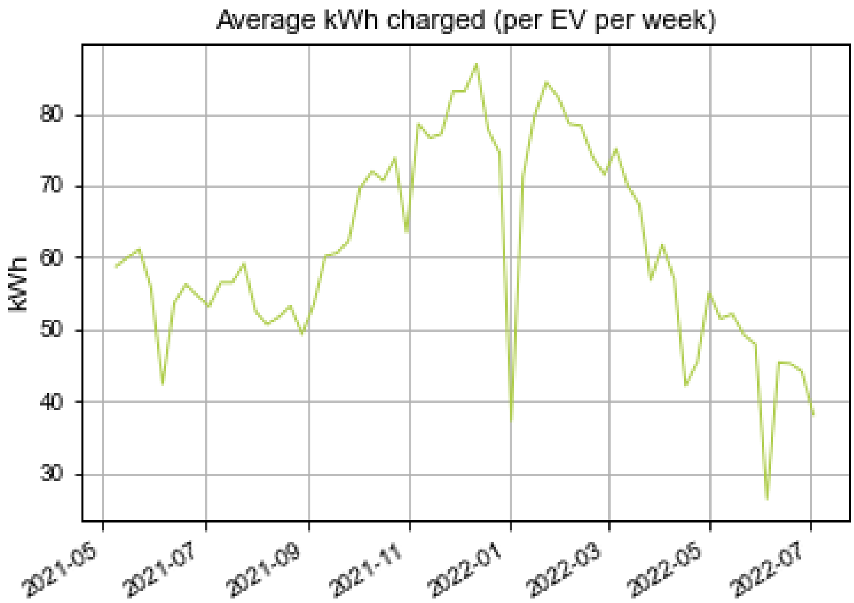
The volume of load varies by location of driver, as shown in Figure 24. This aligns with the average shift distance for each type of route, as presented in Table 3. The timing of the load peak for each location type is remarkably similar, all peaking at approximately 19:00.

Figure 24 – Charging load by location type



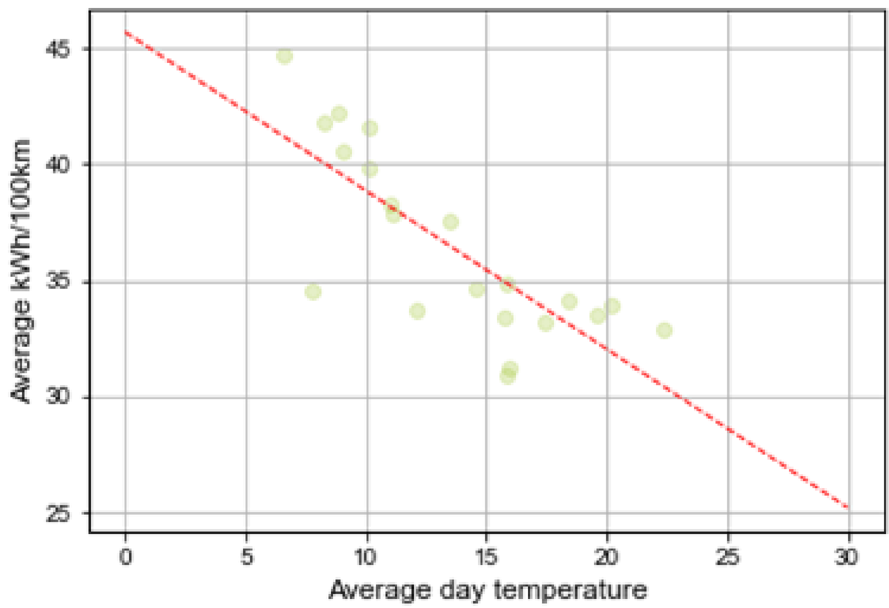
The seasonal variation in weekly charging load, per vehicle, can be seen in Figure 25. There is a clear pattern in load over the year, with a peak in load over the winter months (with the exception of the Christmas/New Year holiday period) which is about 50% higher than in the summer months. While the operational analysis did show increases in journey length and shifts per 1,000 vehicles, the change in EV load is more pronounced and is likely also influenced by the reduced efficiency of EVs in the winter months.

Figure 25 – Seasonal variation in charging load



This can be confirmed by the analysis in Figure 26, which shows how the average efficiency of vehicles varies with temperature. The red dashed line is the average of the points and shows a reduction in range of approximately 7% for each 10ºC change in temperature.

Figure 26 – EV efficiency vs average daily temperature (ºC)



1.3.2 Load impact of smart charging

Centrica also trialled smart charging of the British Gas EVs. In these trials, charging was optimised against supply cost, presuming sufficient flexibility existed (i.e. bounded by the need to fully charge all of the EVs by a set time in the morning).

Figure 27 – Load impact of smart charging

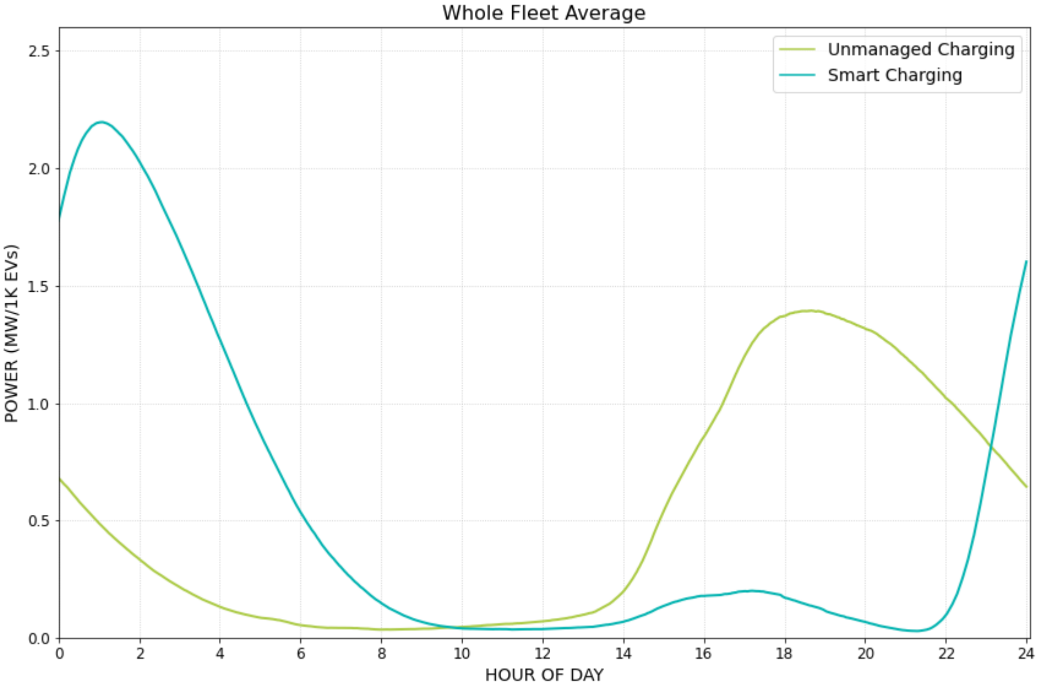


Figure 27 shows the load curve from smart charging, compared with the load curve from unmanaged charging. With smart charging, the evening charging peak is reduced from 1.4 MW to 0.2 MW per 1,000 EVs. The charging is shifted to the 21:00-05:00 period, peaking at 01:00. This charging peak, at 2.25MW, is 80% higher than the unmanaged peak.

The graphs in Figure 28 and Figure 29 show that smart charging can be applied equally well to vehicles doing different shift types and in different locations to avoid evening peak load. However, the different peaks of the groups become aligned, increasing the average peak load overnight.

Figure 28 – Smart charging load by shift type

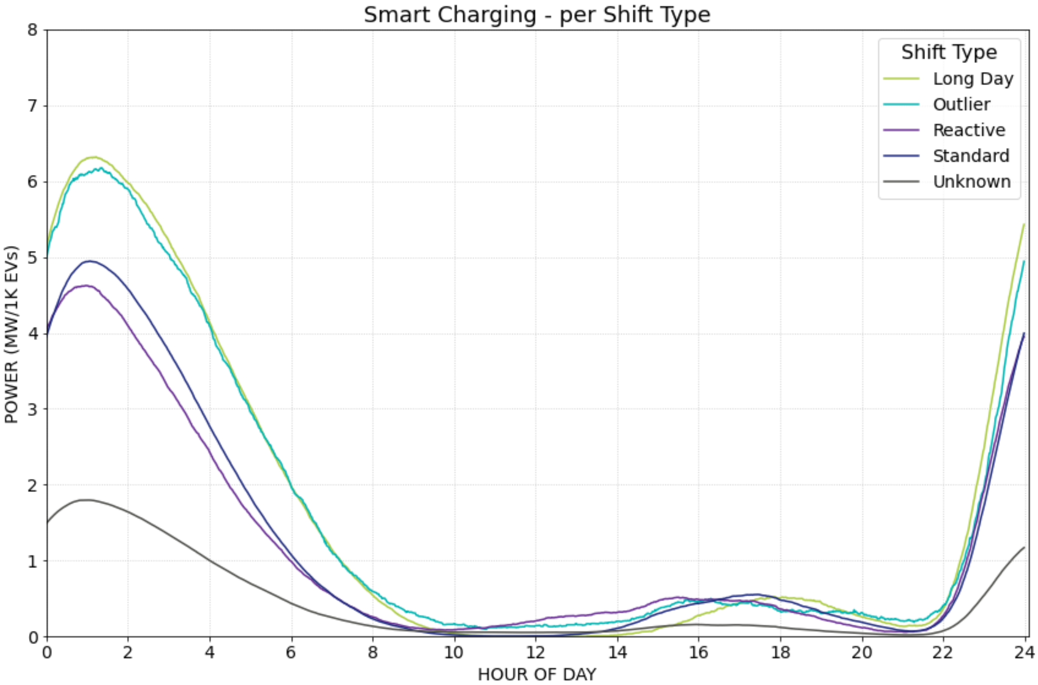
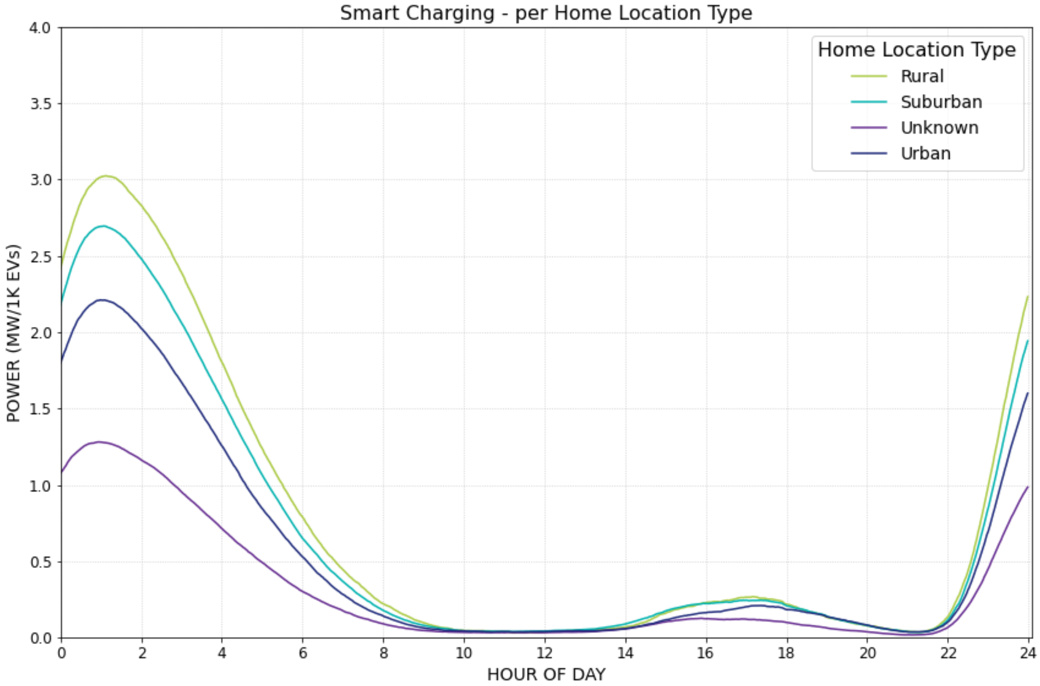


Figure 29 – Smart charging load by location type



1.3.3 Geographical distribution of load from charging of British Gas EVs

Figure 30 and Figure 31 show the average load from the British Gas fleet on the networks in the south-east and nationally, respectively, at local authority level. The pattern is aligned to the home location of British Gas drivers.

The seasonality of this charging activity is shown in Figure 32, for the four licence areas in the south-east, showing the winter peak in charging from the British Gas fleet.

Figure 30 – Average load density from British Gas vans in the UK Power Networks and SSEN regions

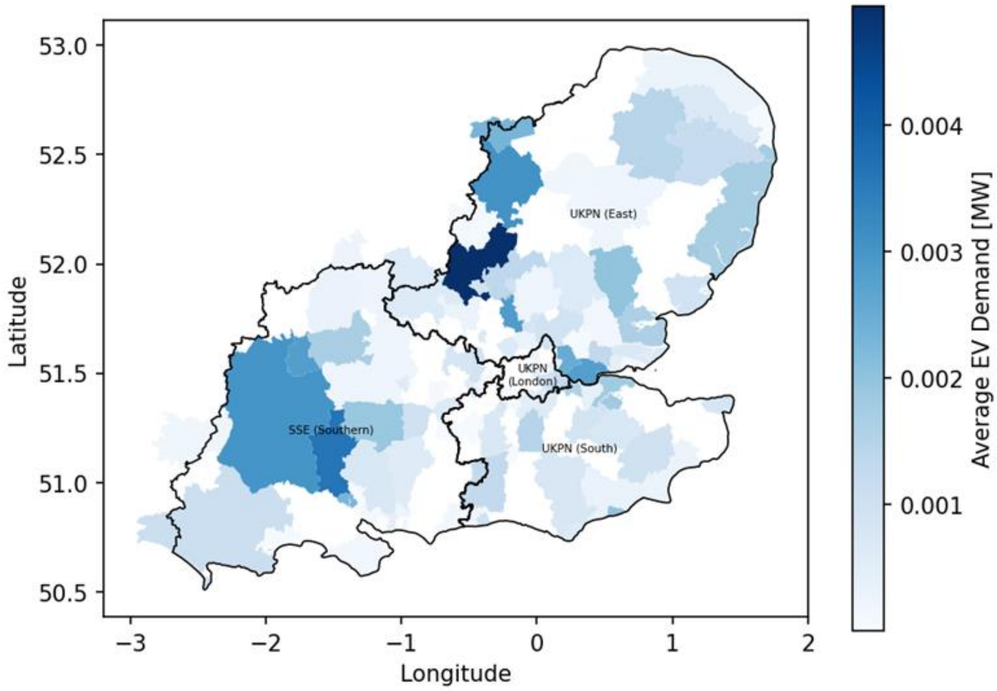


Figure 31 – Average load density from British Gas vans throughout the UK

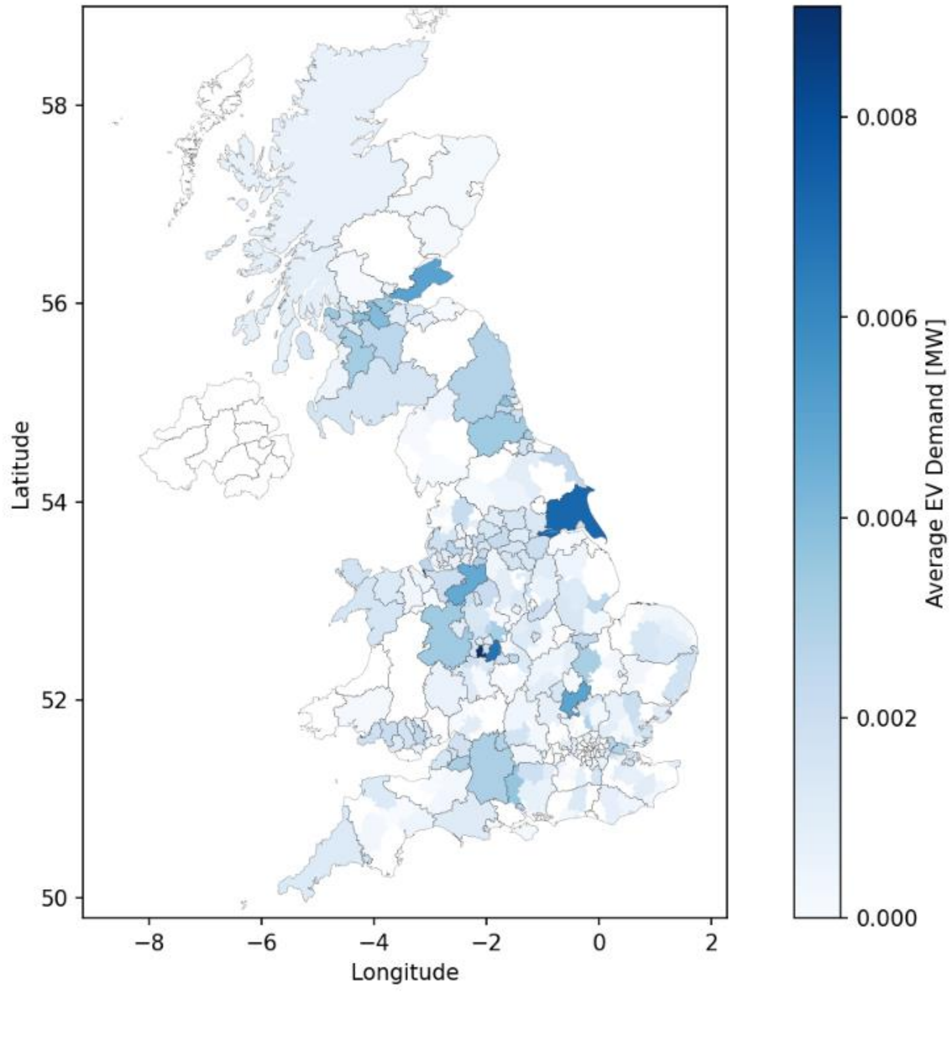
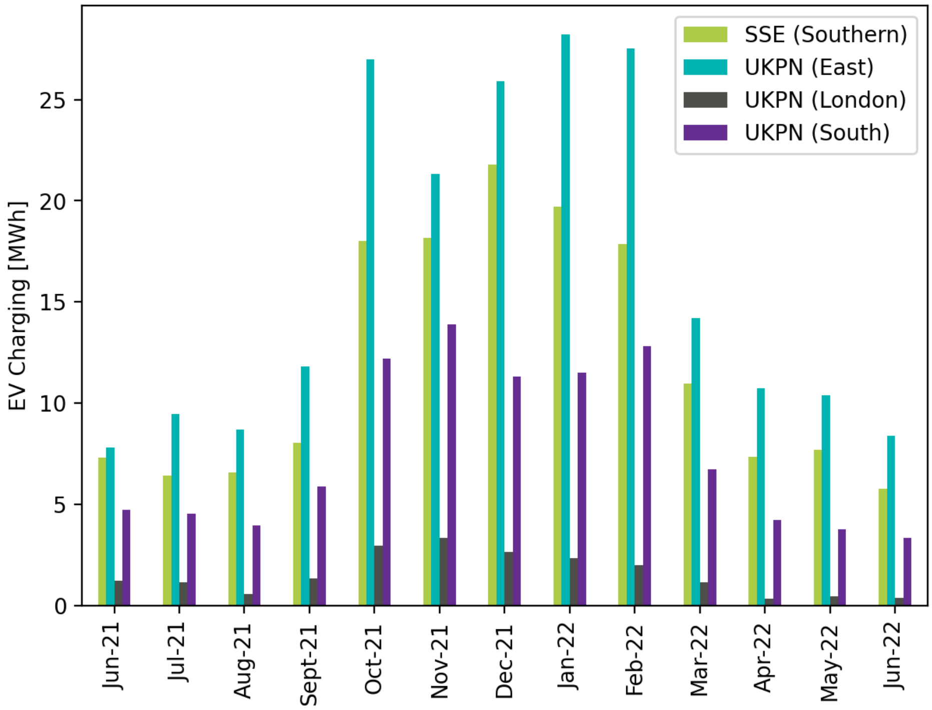


Figure 32 – Seasonal Variation in British Gas charging volume, per license area, per 1,000 EVs



1.4 Future forecasts

1.4.1 Growth scenarios

Centrica created three growth scenarios for the British Gas Fleet:

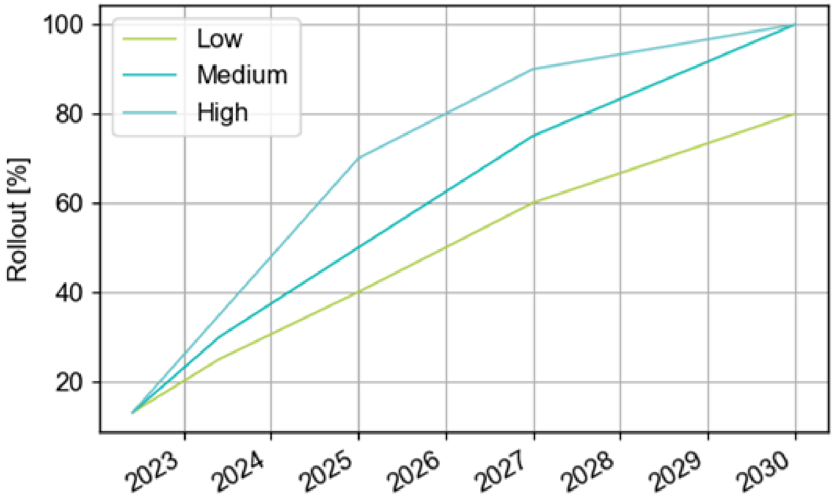
- **Low**: In case of issues with ordering or timely delivery of vans
- **Medium**: Current planning used by the Fleet team
- **High:** In case Centrica's or the government's ambitions for Net-Zero accelerate

Table 5 details the projected fleet growth in each of these scenarios and Figure 33 illustrates the relative growth scenarios.

Table 5 – British Gas Fleet EV growth scenarios

EV share	July 2022	Q2 2023	2025	2030
Low	13% (1135)	25% (2,125)	40% (3,400)	80% (6,800)
Mid		30% (2,550)	50% (4,250)	100% (8,500)
High		35% (2,975)	70% (5,950)	100% (8,500)

Figure 33 – British Gas fleet electrification scenarios



1.4.2 Future fleet load growth

Based on these forecasts and the average load curves from the trials, it is possible to predict the power energy demand of the fleet, at different points in time, in an unmanaged scenario. Figure 34 shows the forecast daily demand curves for 2023, 2025 and 2030. In the high and medium scenarios, the fleet's nationwide power requirement would peak at just under 12MW at around 18:30.

Figure 34 – Forecast power demand from the British Gas fleet in an unmanaged scenario

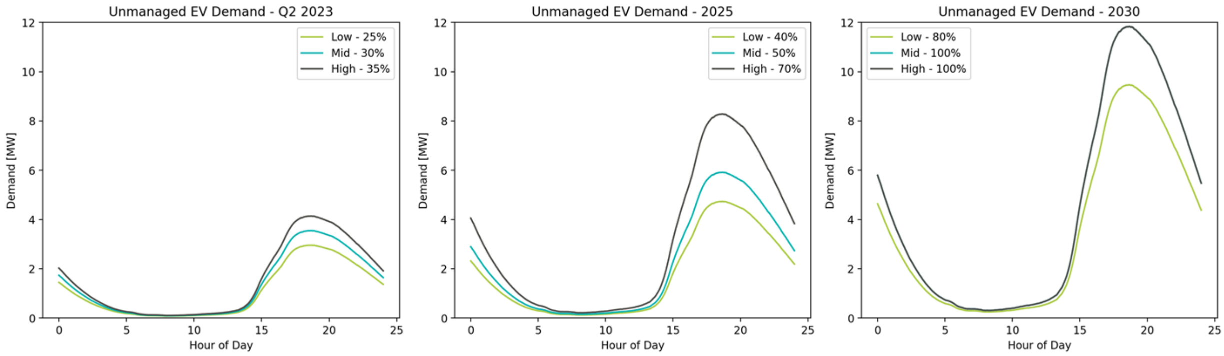
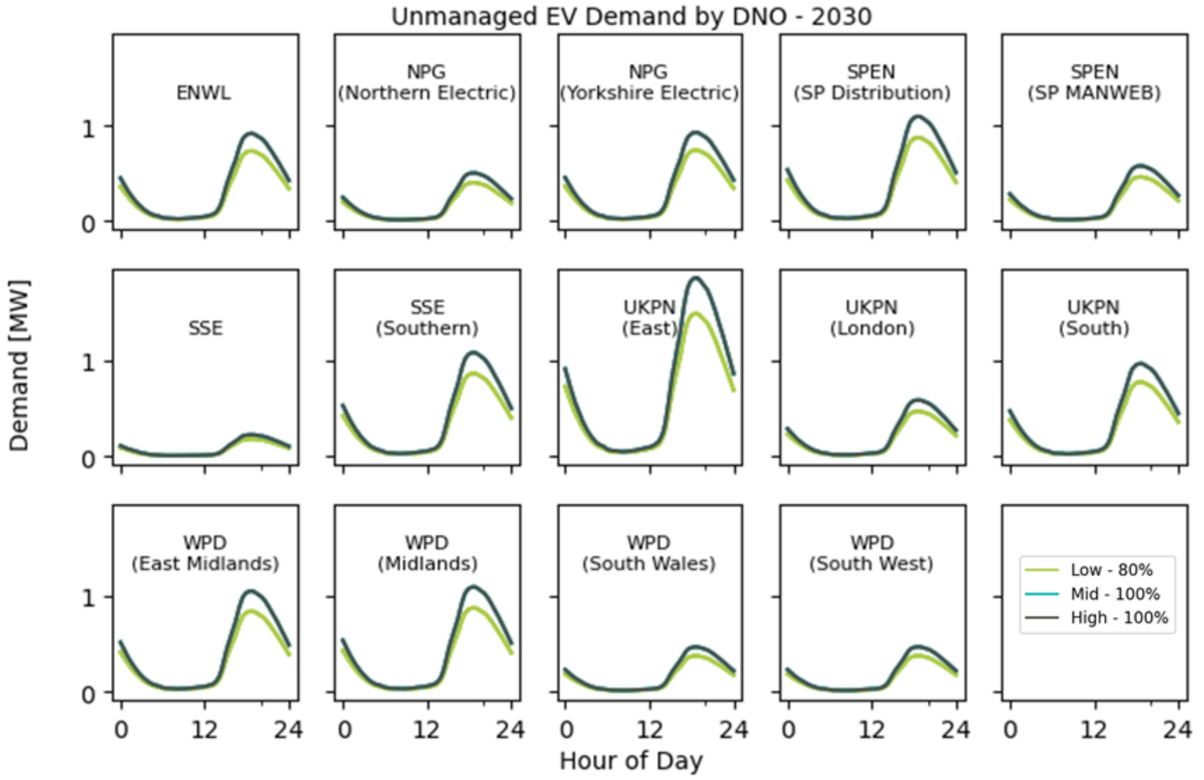


Figure 35 shows how each DNO area in GB would be impacted by British Gas' electrification, based on the current location of drivers. While the load shape is the same, the scale of the impact varies due the location of drivers.

Figure 35 – Forecast 2030 power demand from British Gas fleet, by DNO area



If smart charging were to be implemented, to shift all charging to the cheapest time of day, the peak load could be shifted away from the peak time of 18:30. However, as noted in section 1.3.2, this type of strategy can result in a significant secondary peak. Table 6 shows how, once the full fleet is electrified, a secondary peak of 18.65MW could be created at 01:00 in the smart charging scenario, 50% higher than the unmanaged peak.

Table 6 – Forecast peak loads from unmanaged and smart charging

Fleet electrification [%]	Unmanaged peak load [MW] at 18:30	Smart charging peak load [MW] at 01:00
20%	2.37	3.73
50%	5.92	9.33
80%	9.47	14.92
100%	11.84	18.65

2 WS2 – Depot trial

The depot trials collected data from vehicles and chargers in order to analyse the charging patterns of depot-based commercial vehicles.

2.1 Data collected

A wide range of data points were collected to inform the analysis and carry out the Optimise Prime methods. The following data was collected and published in Deliverable D6:

Table 7 – Data collected in WS2

Dataset	Source	Data
Trial Asset Data	Royal Mail	Details of each depot, CP/socket and EV involved in the trials. Specifications of each type of EV and CP used by Royal Mail at the trial depots.
Telematics Data	EV telematics systems	Details of each journey made by the EVs in the trial. Details vary due to the multiple telematics systems in use, but generally include start/end times of trips, distance travelled, battery state of charge, details of charging sessions.
Building Load	Panoramic Power monitoring	The electrical load recorded at each depot at a one-minute frequency.
CP Measurements	CP management system	Reporting of CP status (e.g. whether the CP is available or charging, whether an EV is connected); Periodic reporting of the total energy delivered (meter in kWh), real power (instantaneous load in kW) and the current limit (the maximum charge speed set, in amps).
Trial Data	Trial Systems	Data relating to the nature and duration of trial events, including profiled connections and flexibility dispatches, was captured.

The trials also made use of a number of additional data sources, including monitoring on the network side of the connection to measure profiled connections.

2.2 Operational analysis

Deliverable D4 presented an initial operational analysis based on early data collected from the Royal Mail ICEV fleet and EVs. This section expands upon that analysis.

In Deliverable D4, operating schedules were derived for each depot, from telematics, as a means of predicting the EV load resulting from EV charging. This analysis was based upon the start and end times of trips in the telematics data. In this further analysis, data from the full trial period has been used and a new method of clustering individual trips into schedules has been developed.

Key considerations in this new method include:

- Treating an EV as on a trip when it travels more than 0.1 miles from a depot
- Analysing stops in the vehicle's schedule, where an EV returns to the depot for 45 minutes or longer during the day
- Assigning each vehicle a schedule for the day, rather than treating trips independently
- Limiting the analysis to Monday-Saturday due to the significantly lower levels of trips on Sundays

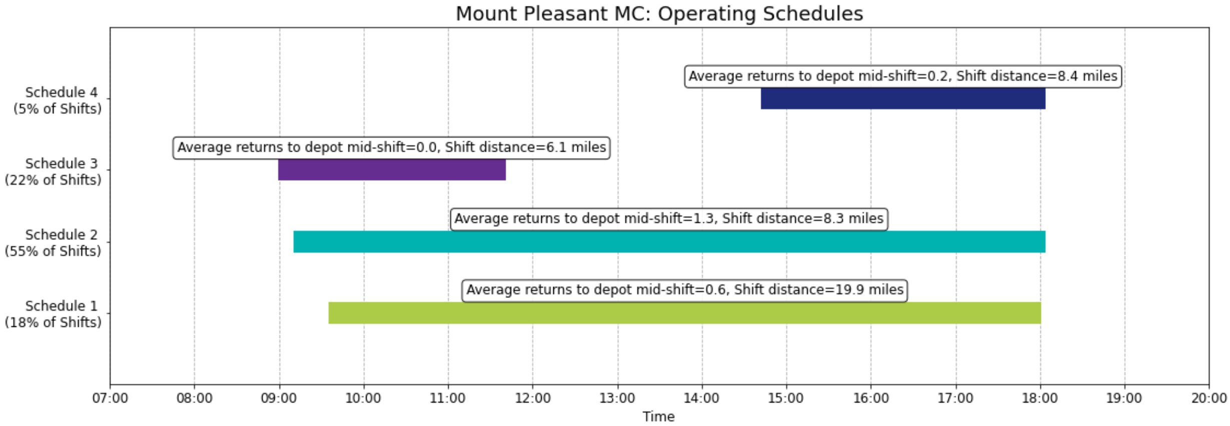
The clustering of trips takes the following features into account:

- First departure time
- Last return time
- Miles travelled
- Number of returns to depot (time > 45mins)

2.2.1 Analysis and grouping of Royal Mail Operating schedules

The analysis of the EV schedules, at Mount Pleasant Mail Centre, in Figure 36, illustrates the four EV shift types observed at the site. It shows that 73% of the vehicles at the depots operate for a full day, from approximately 09:00 to 18:00, likely including delivery and collection duties, and hence only three-quarters of the fleet might be available for flexible turn down services at peak network times, which is important when forecasting flex bids. However, there is difference within these vehicles – 18% of the EVs are likely to stay away from the depot all day and complete over twice the mileage of the 55% of vehicles that return at least once during their shift. The remainder of the vehicles complete either a morning delivery shift, returning before 12:00 (22% of total fleet) or an afternoon collection shift, not leaving the depot until 14:30 on average (5%).

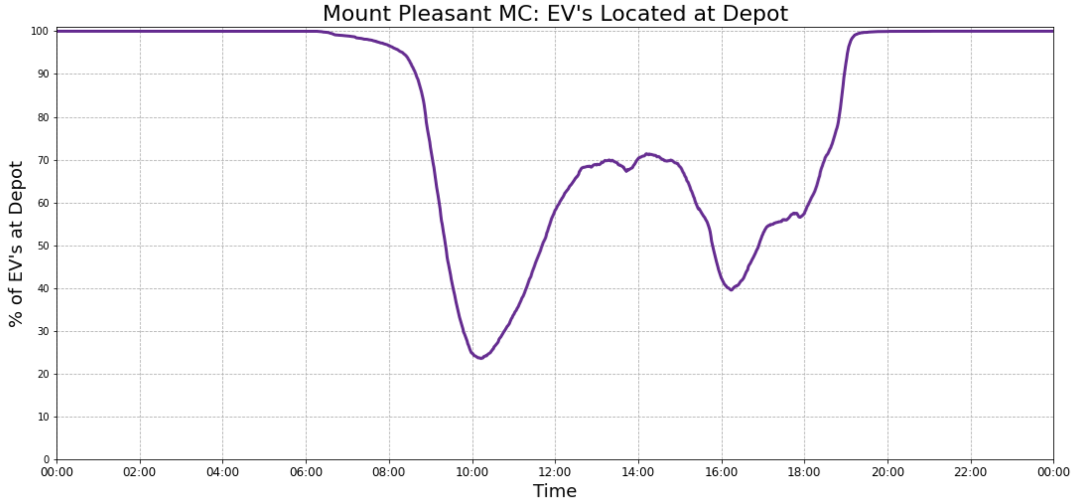
Figure 36 – Operating schedules at Mount Pleasant Mail Centre



This analysis shows the number of EVs present at the depot, and potentially able to provide flexibility services, varies over time, and that EVs may be able to charge during the day as well as at the end of the day, given the early and late shifts and the mid-shift breaks.

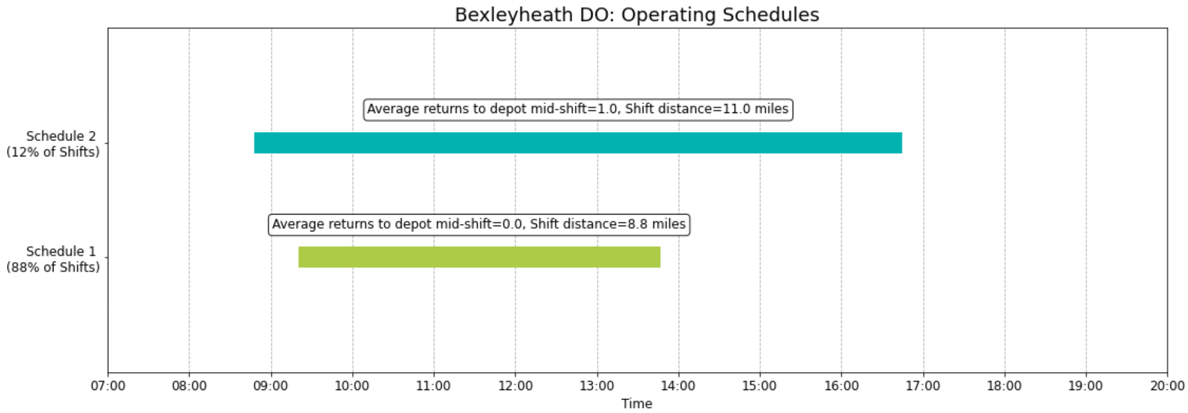
Figure 37 shows the proportion of vehicles that are present at the Mount Pleasant Mail Centre throughout the day. This highlights that the full charging capacity of the site is unlikely to be reached until after 19:30 in the evening, and that there is a potential for charging EVs in the early afternoon when drivers are between shifts, outside of network peak times.

Figure 37 – Proportion of EVs at Mount Pleasant Mail Centre over an average day



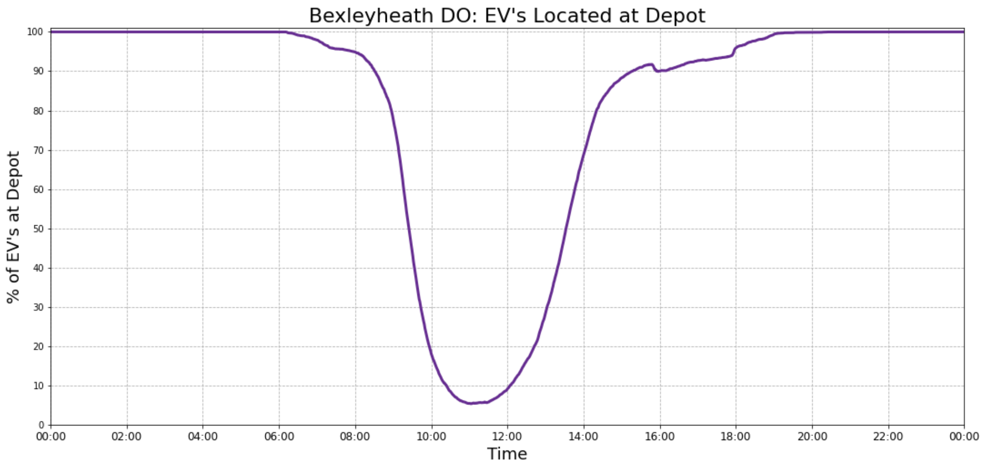
Although Royal Mail depots carry out similar work, the pattern of shifts varied significantly. For example, at the suburban Bexleyheath depot only two shift patterns were identified, as shown in Figure 38. The majority of vehicles performed a single morning shift, while a smaller group of vehicles had an all day schedule, with a mid-shift return to depot.

Figure 38 – Operating schedules at Bexleyheath Delivery Office



This results in a markedly different pattern of depot occupancy, as shown in Figure 39, with no mid-shift peak, but 90% of EVs being back at the depot from 15:00 and hence better positioned to offer flexibility services during peak hours.

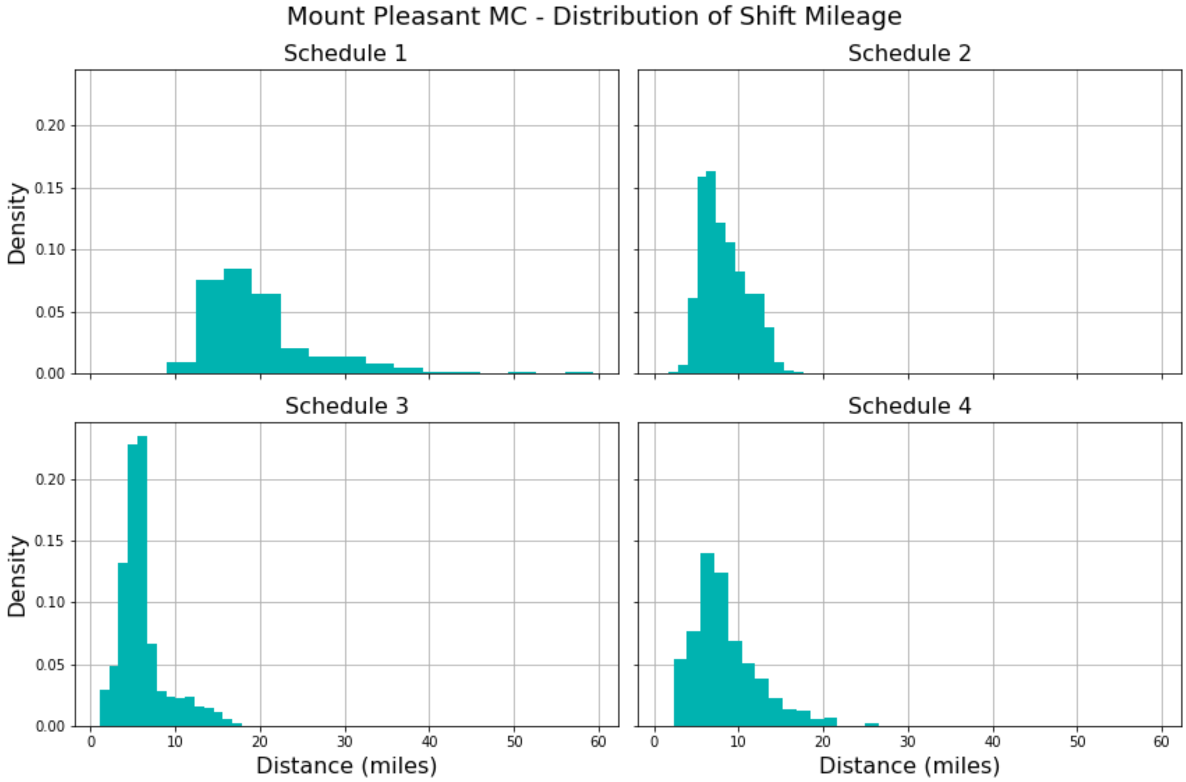
Figure 39 - Depot occupancy, Bexleyheath



2.2.2 Variations in distance in operational schedules

In addition to the lengths of the shifts and return times, journey distance is also important in predicting charging load on the electricity network, or ability to flex load. Figure 40 shows the range of distances within each schedule at Mount Pleasant. While most mileages (the % density) are relatively low, some vehicles travel over twice as far as the average, but none more than 60 miles in a day).

Figure 40 – Shift Mileage Distribution, Mount Pleasant Mail Centre



2.2.3 Conclusions

The project concludes that telematics data could be used to infer the plug-in times of vehicles at a site. This enables the potential EV charging load profile to be forecasted.

Telematics data can also be used to identify periods when vehicles are at the depot but not plugged in. If there is a requirement to reduce the peak charging load to later in the day, these stops at the depot may be suitable for charging vans mid-shift.

However, telematics data aggregated to daily summaries, as was used in the first iteration of the operational modelling of the diesel fleet, is not sufficient to identify accurate operating schedules. Granular telematics data is needed in order to identify the unique characteristics of each operating schedule (such as returning mid-shift and movement within the depot).

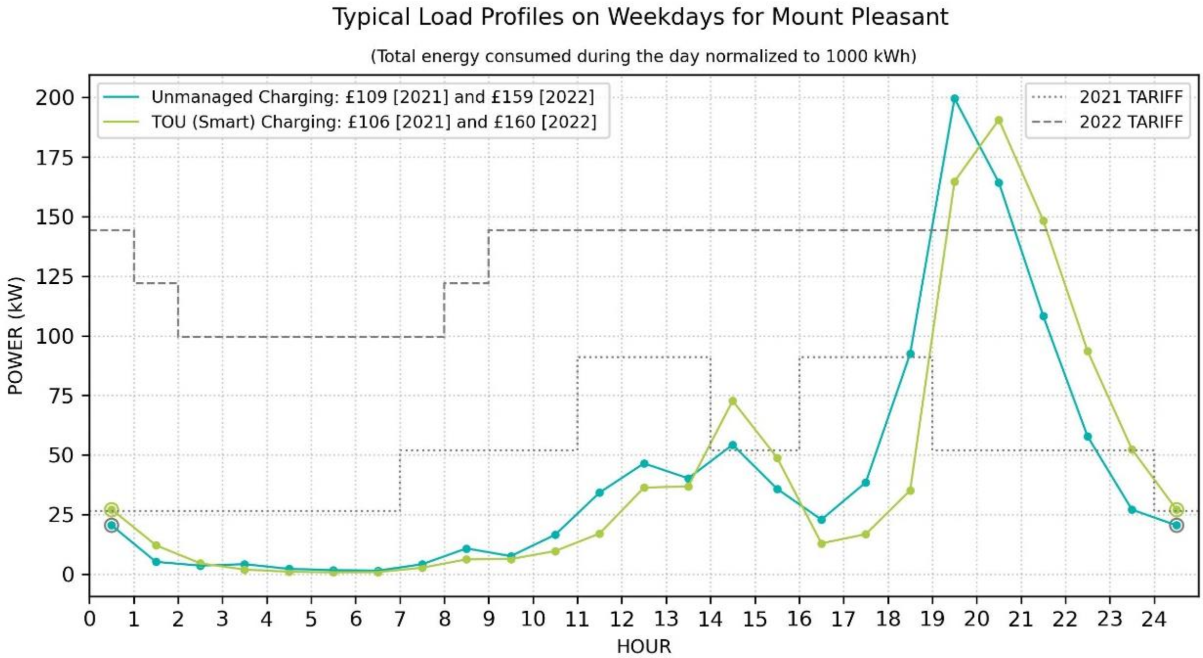
2.3 Load profile analysis

Electrical load from EV charging was monitored at Royal Mail depots throughout the trial period. This section explores patterns in the observed load across a variety of scenarios, considering how this load relates to vehicle operations.

2.3.1 Load from unmanaged and smart charging

Figure 41 shows the normalised load across the day at the Mount Pleasant Mail Centre. The lines on the diagram show the average results from two different scenarios – unmanaged charging and time-of-use tariff based smart charging. In the latter scenario, charging power is reduced when electricity tariffs are higher. The dotted line shows the tariff bands that are used to calculate the optimisation.

Figure 41 – Typical unmanaged and smart charging load at Mount Pleasant Mail Centre

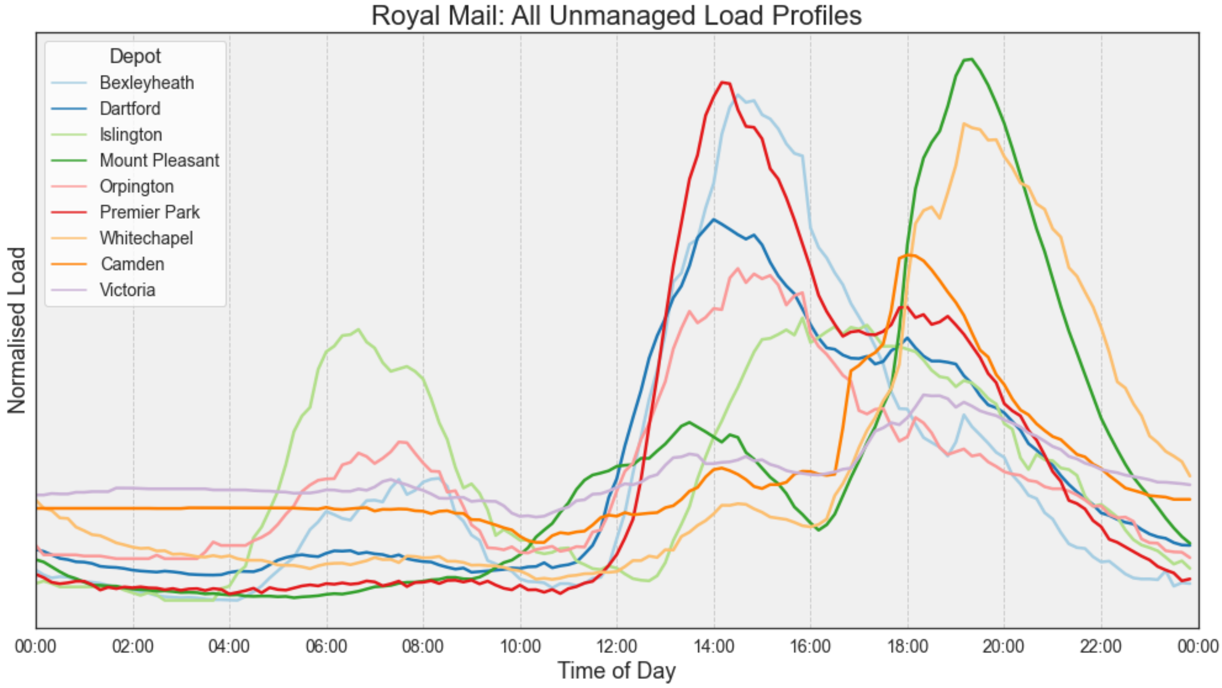


A change in load shape can be seen, specifically shifting peak load slightly later. However, the scale of the impact of smart charging is limited at this location. This is driven by two factors:

- The minimum charging speed of six amps per vehicle means that charging cannot be delayed to the cheapest overnight periods, because many vehicles will have completed charging earlier, even at the minimum rate.
- The unmanaged charging at Mount Pleasant does not peak when the electricity prices are highest. At other depots, with earlier evening peaks, the ability to shift demand is greater.

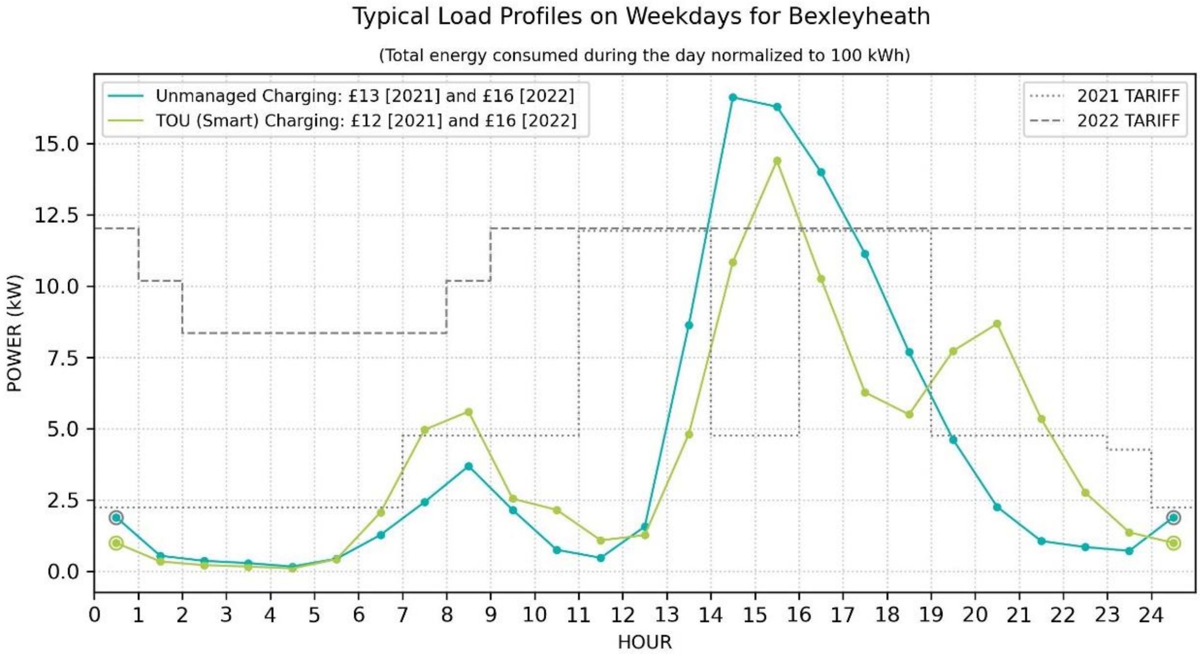
A similar pattern can be seen in the impact of smart charging. However, it is notable that the load shape varies across the depots in the study. Figure 42 overlays the average normalised load shapes of the nine Royal Mail depots.

Figure 42 – Normalised load shapes of Royal Mail depots



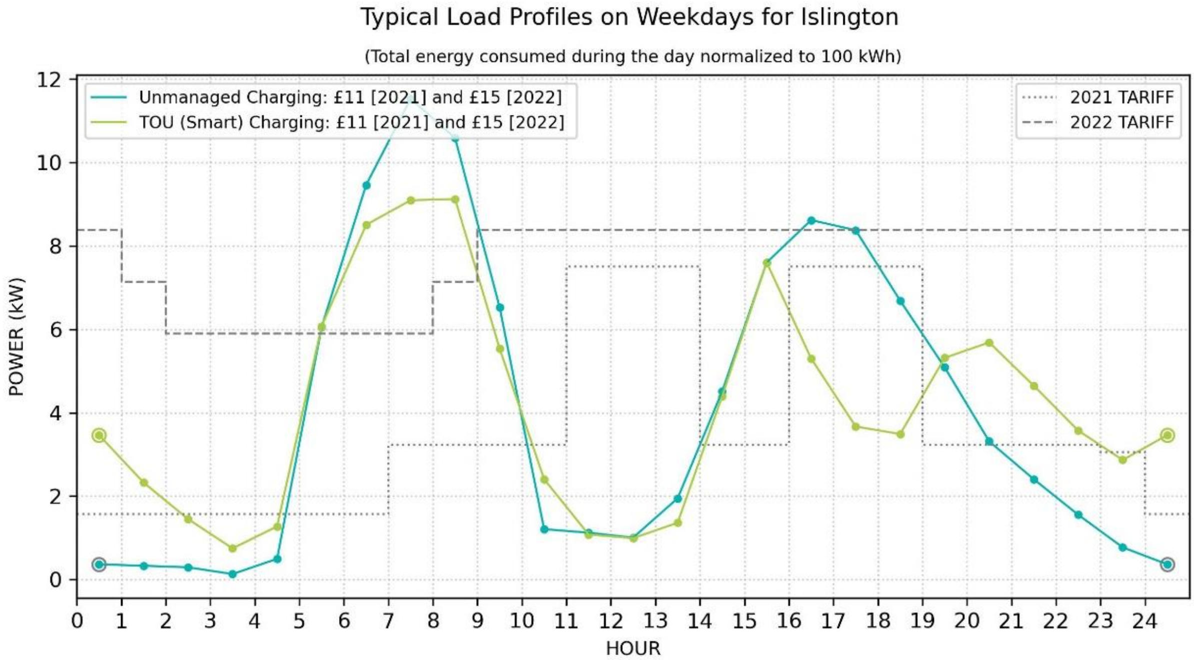
There are similarities in the general shapes of the load, yet the timing of the load peaks varies significantly. Urban depots, such as Mount Pleasant, generally have peaks later in the day and rural/suburban depots have shifts that end earlier, resulting in peak demand in the early afternoon, as can be seen in the case of Bexleyheath in Figure 43.

Figure 43 – Average load patterns at Bexleyheath Delivery office



Different working practices can also impact the pattern of EV load. Some depots had a single daily peak, in unmanaged charging, while some depots had an additional mid-day peak, relating to vehicles returning to the depot and then leaving again, as at Mount Pleasant. The primary peak at the Islington depot was in the early morning, when vehicles were plugged in before the start of the shift, as shown in Figure 44.

Figure 44 – Average load profiles at Islington delivery office



This significant variation highlights the need to consider each site within a business separately, even if the type of site is similar when planning electrification, and when considering when would be appropriate to take part in services such as flexibility or dynamic profile connections.

2.3.2 Seasonal variation in charging demand

In addition to the variation between each depot, the unmanaged load at each depot can vary significantly from day-to-day or over time. Different depots saw are large variation in charging demand, ranging from around 15% at Dartford to over 30% at Islington.

Figure 45 – Variability in unmanaged load at Dartford

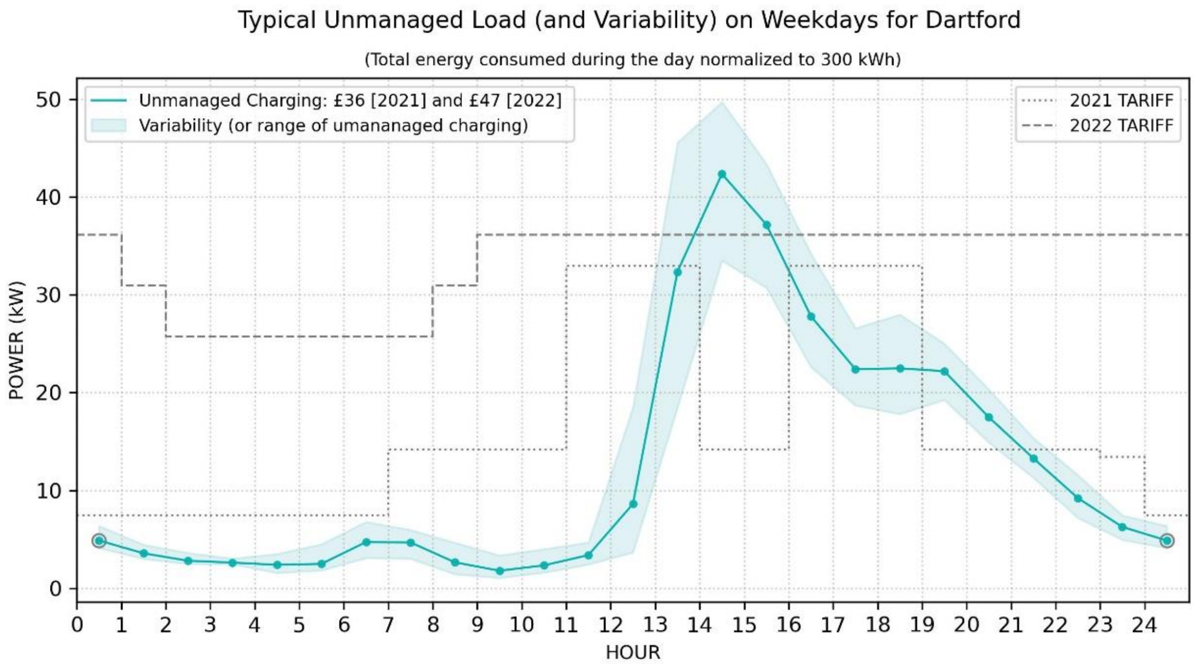
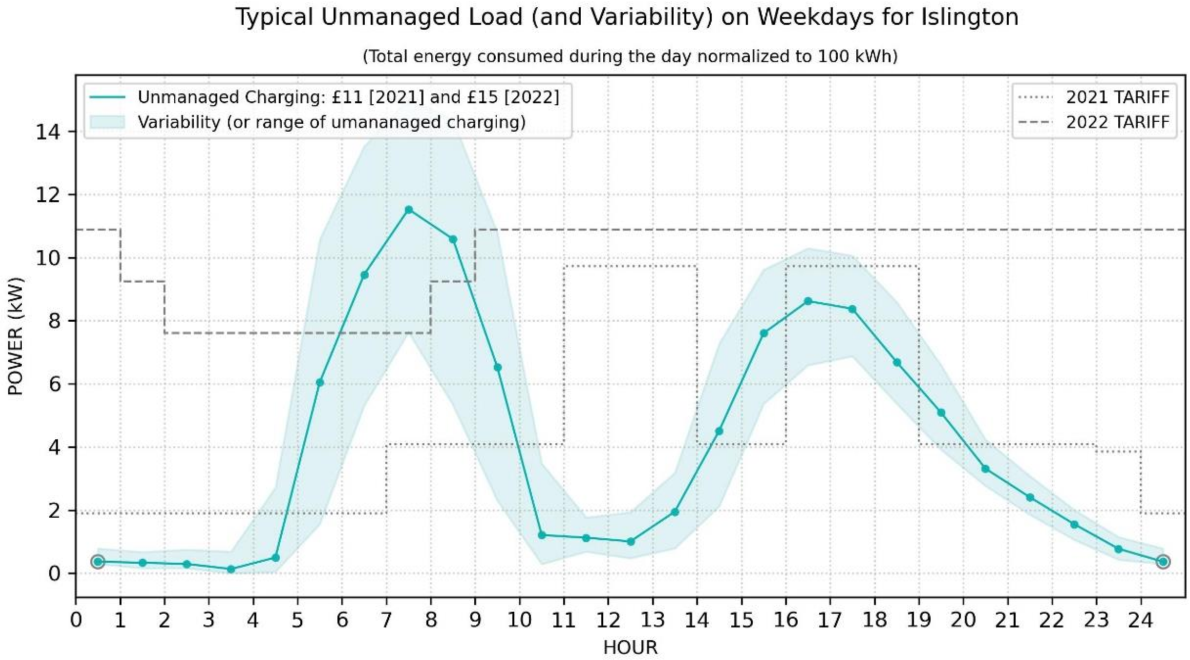
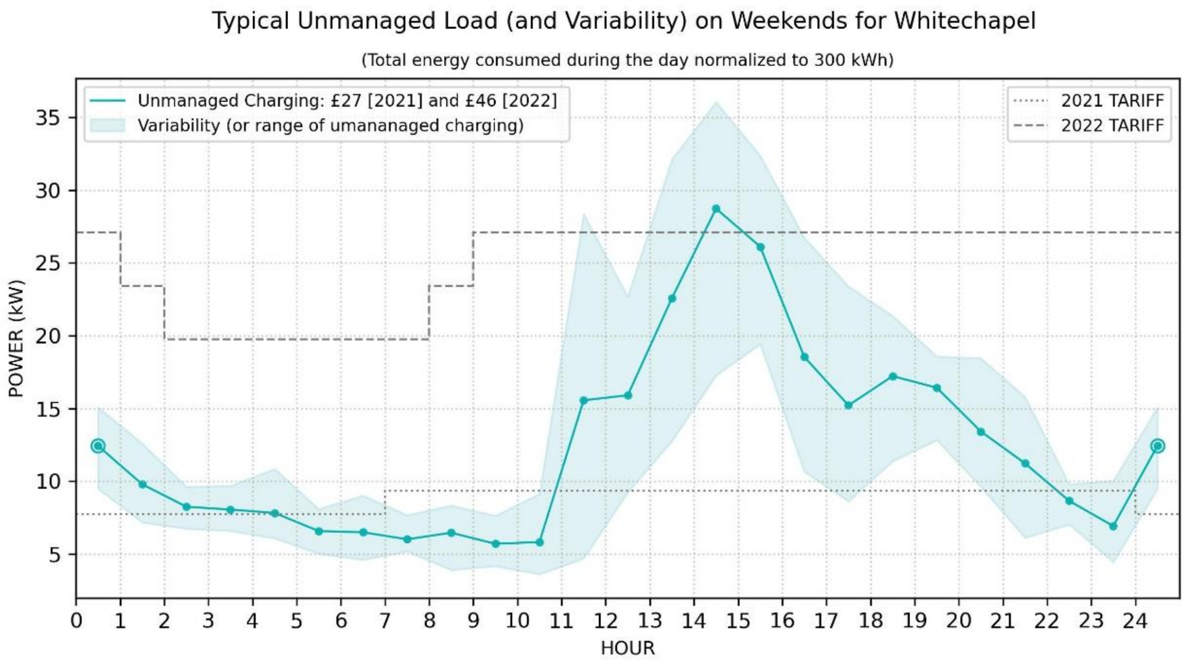


Figure 46 – Variability in unmanaged load at Islington



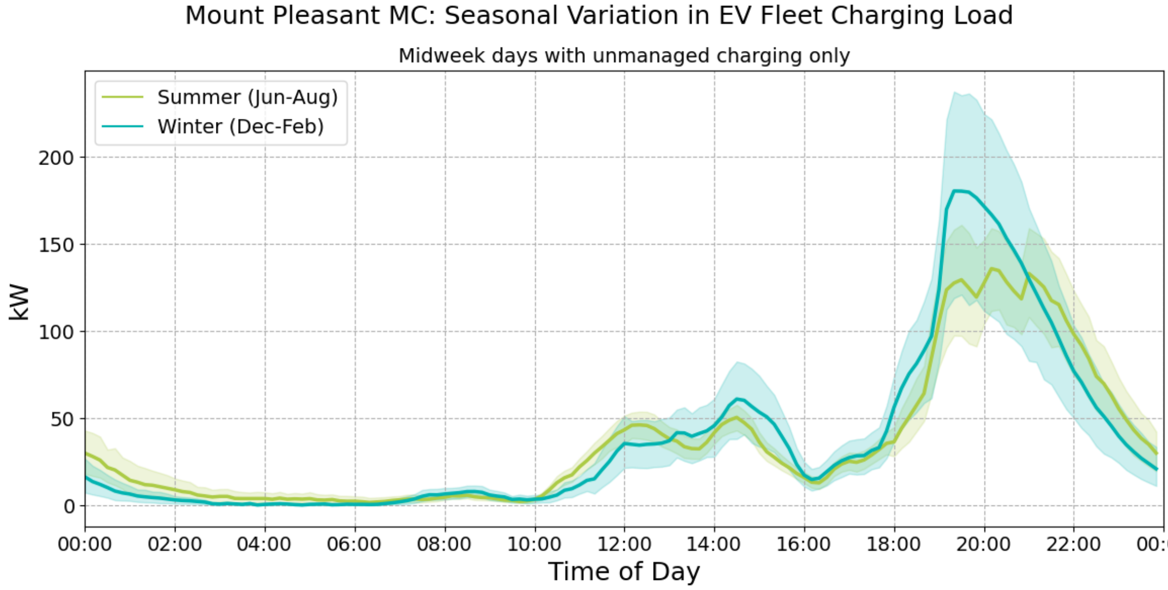
At weekends, load patterns are significantly different to weekdays, with many depots seeing negligible charging on Sundays. On Saturdays, load was found to be of lower magnitude, earlier in the day and less predictable, as shown for Whitechapel Delivery office in Figure 47, again with a significant variability.

Figure 47 – Weekend load variability at Whitechapel



Across the trial depots, average daily load, in the winter months, was 26% higher than in the summer months, with changes at individual depots ranging from 6% to 66%. It should, however, be noted that some depots, especially those with the largest percentage change, added additional vehicles to their fleets part way through the year. Figure 48 shows the difference in average unmanaged load, at Mount Pleasant, and the range of load, demonstrating that winter demand is both higher and more variable.

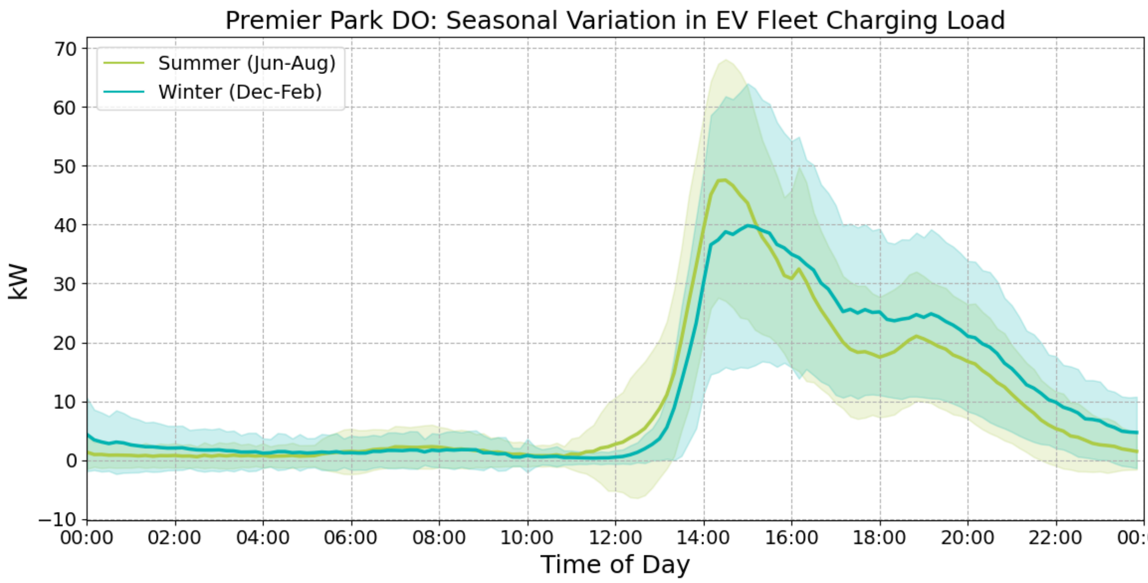
Figure 48 – Mount Pleasant unmanaged load - Summer vs Winter



This variation is due to a combination of vehicles travelling further (at Mount Pleasant, shift distances are 0.6 miles longer in the Winter), the timings of shifts being slightly different, and the vehicles being less efficient. On average, each vehicle at this depot requires 1.6kWh more energy per day in the winter period (around 23% more).

While the pattern of higher demand, in the winter, resulting in higher peak loads applies to most depots studied, there was an exception. At the Premier Park delivery office, the average load across the day was 9% higher in the winter. However, vehicle plug in times at the depot shifted by two hours earlier, and were more concentrated, in the summer. This resulted in a peak load that is 19% higher in the summer, as shown in
Figure 49.

Figure 49 – Seasonal variation in charging load at Premier Park Delivery Office

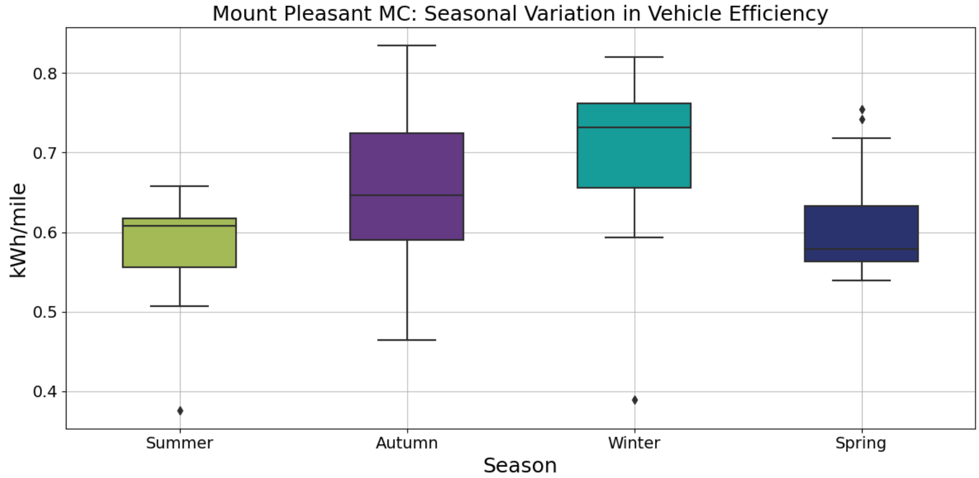


2.3.2.1 *Variations in vehicle efficiency*

Across the whole fleet, 31% more energy (to 8.5 kWh/day/EV) was required per mile, in the winter, than in the summer. The change in efficiency also varies between depots – between

20% at Mount Pleasant (Figure 50) and 46% at Orpington. The difference in efficiency is likely to be driven by a range of factors, such as use of heating, increased payloads, rain and the impact of colder weather on battery chemistry.

Figure 50 – Seasonal variation in vehicle efficiency – Mount Pleasant



2.3.3 Impact of LCTs on EV load

While there are limited amounts of LCTs, such as solar photovoltaic panels, installed at some of the Royal Mail depots, it was not possible to measure their impact on site load during the trial.

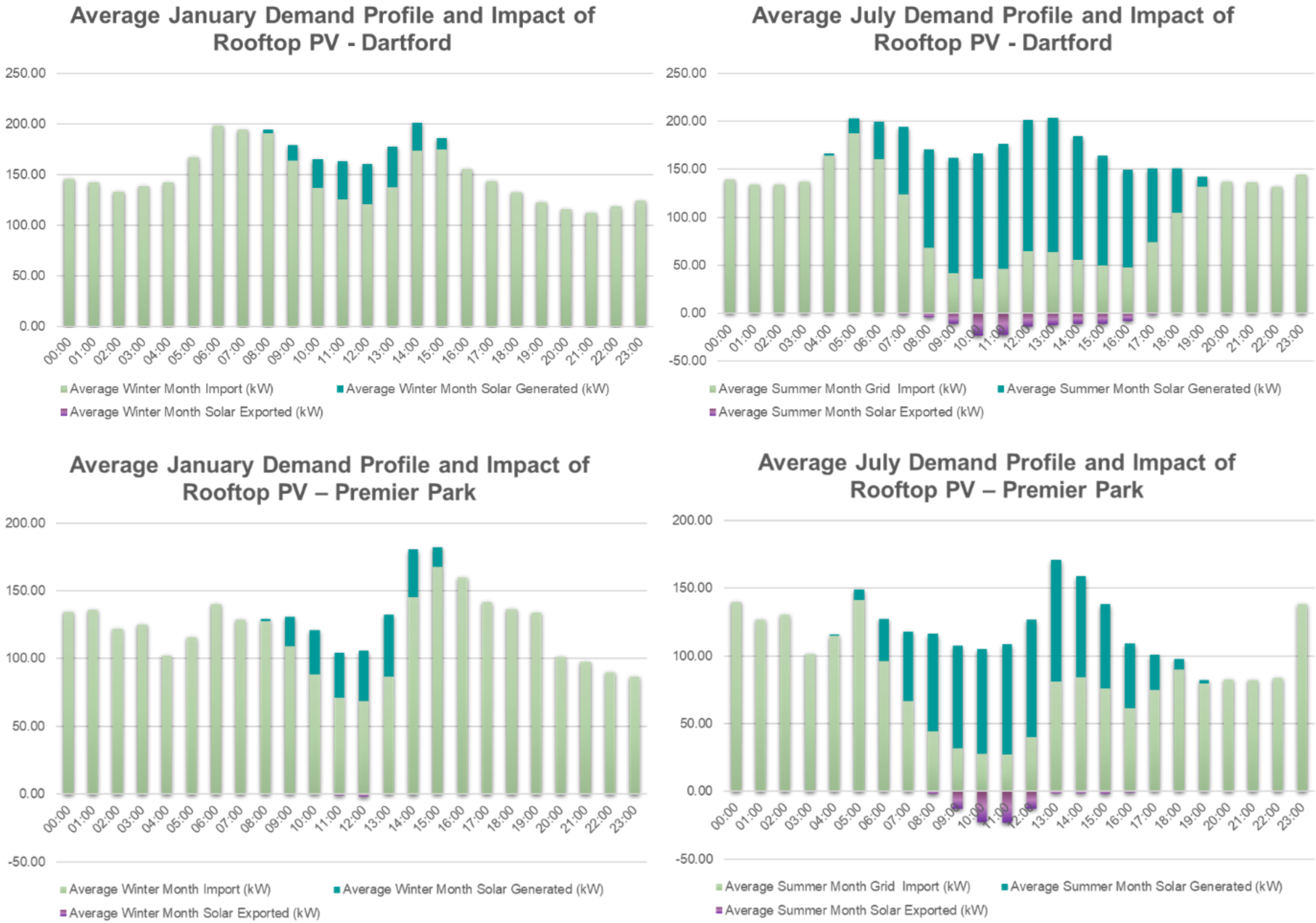
Optimise Prime analysed the potential for solar power and battery energy storage systems at two Royal Mail depots – Dartford and Premier Park – and compared it to the load at these sites. It was not possible to do this for all depots, because some had complex layouts/roof structures which made estimating the potential for solar installation difficult without a full survey.

The Dartford site was estimated to be able to support a solar array with a capacity of 350kWp, while the Premier Park site could support a 210kWp array (Figure 51).

Figure 51 – Example of modelled PV array at Premier Park depot

Imagery ©2022 Google ©2022 Maxar Technologies, The Geoinformation Group, Map Data ©2022 Google

Figure 52 – PV and demand profiles for Dartford (above) and Premier Park (below) depots



In both cases, the sites were able to utilise the vast majority (over 90%) of the produced power (shown in Figure 52) during the day, and as a result, there is likely to be little benefit in installing battery energy storage system (BESS) at these locations.

At both sites, the business case for installing solar PV panels was found to be positive, with a payback period of three to four years on the investment.

Optimising the charging of vehicles further according to LCT generation is likely to be ineffective because:

- At the time of peak generation, in the middle of the day, most vehicles are likely to be away from the depot for operational reasons. Vehicles already begin charging when they return in the afternoon, so cannot have their charging shifted earlier.
- The depots can self-consume most of the electricity, generated during the day, saving on cost of electricity at this time. In the winter months, all electricity generated is forecast to be self-consumed. Storing this generation until later in the evening, when more EVs may be charging, could potentially generate some additional savings from peak tariff avoidance, but this is unlikely to offset the cost of the required BESS. A BESS could at the maximum increase self-consumption by around 7%, as shown in Table 8.
- While demand from EVs has been shown to peak in the winter, solar power generation peaks in the summer, making it more difficult to offset load from EVs.

Table 8 – Self consumption rates with BESS at Premier Park Depot

	PV self-consumption rates	BESS Inverter size kW					
		25	50	100	150	200	250
BESS kWh	0	91.07%	91.07%	91.07%	91.07%	91.07%	91.07%
	25	92.58%	92.58%	92.58%	92.58%	92.58%	92.58%
	50	93.73%	93.79%	93.79%	93.79%	93.79%	93.79%
	100	95.15%	95.66%	95.68%	95.68%	95.68%	95.68%
	150	95.52%	96.89%	97.01%	97.01%	97.01%	97.01%
	200	95.74%	97.53%	97.86%	97.86%	97.86%	97.86%
	250	95.80%	97.82%	98.35%	98.35%	98.35%	98.35%

The impact of installation of other LCTs on load profiles of electrified depots can be predicted

The project predicted the potential for on-site generation from solar PV at two Royal Mail depots. While the output of solar PV does vary, it can be predicted relatively accurately. If the load of the site, including EVs is known, this can be used together with the solar PV output calculation to demonstrate the impact of solar PV on EV load.

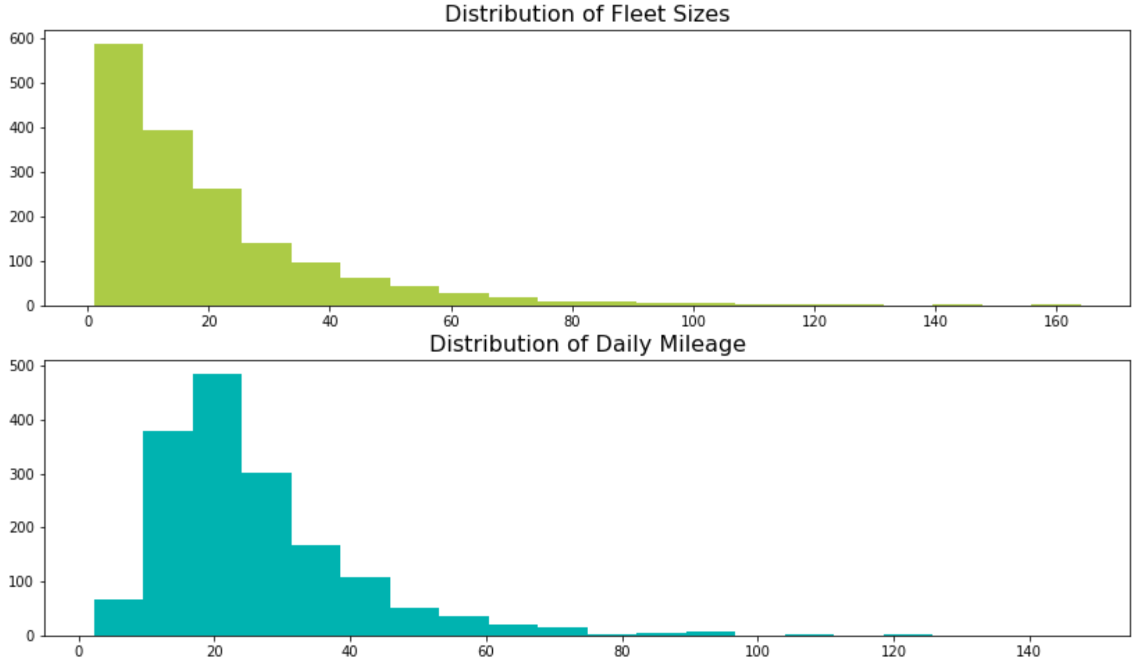
2.4 Future forecasts

Royal Mail intend to electrify their LCV fleet by 2030. This section considers the possible load impacts of the expanded fleet, based on the observed loads at the trial depots.

2.4.1 The existing fleet

The Royal Mail LCV fleet consists of around 33,000 vehicles based at around 1,600 locations across the UK. As shown in Figure 53, there are a wide range of location types, ranging from single vehicles in rural areas up to a maximum of 160 vehicles. Across the fleet there is also a range of daily mileages, from under 10 miles in urban areas, to approaching 100 miles per day in the most rural. The average mileage for a Royal Mail van is just over 20 miles per day.

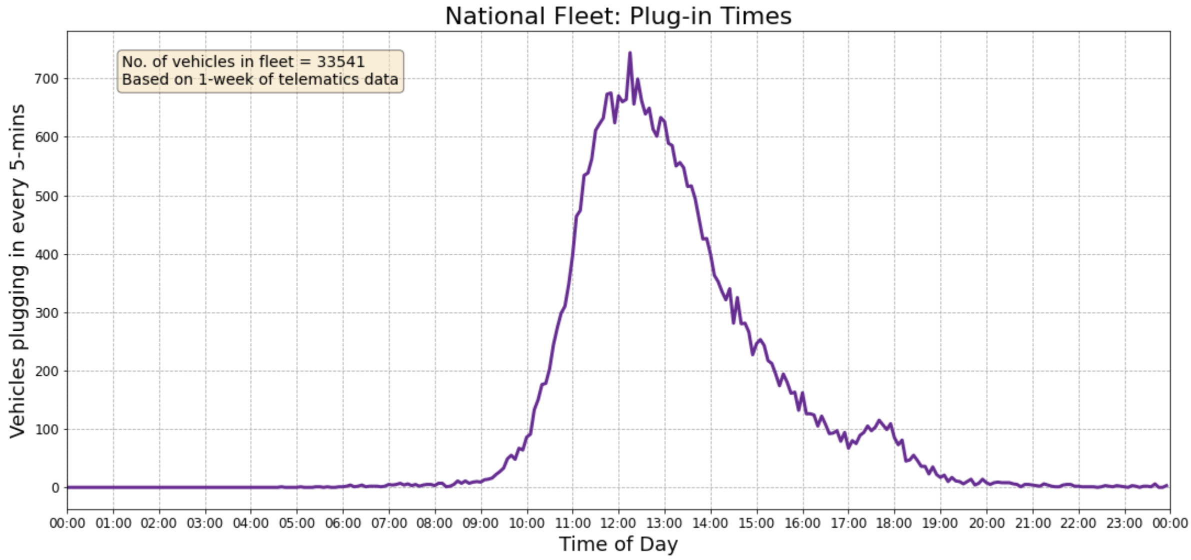
Figure 53 – Distribution of depot sizes and mileages throughout the UK



2.4.2 Forecast charging load

Based on a sample of telematics data from the entire UK Royal Mail fleet, the estimated plug-in time of each vehicle was modelled, as shown in Figure 54. This analysis takes into account the last activity for each van each day and an assumed 2:1 ratio of EVs to CPs. Plug in events occur throughout the day, with a peak occurring just after mid-day, following morning delivery rounds.

Figure 54 – Plug-in times for Royal Mail national fleet



Based on these plug-in times and volumes, together with the distance travelled, an assumed vehicle efficiency of 0.352 kWh/mile is used to predict the resulting unmanaged load on the distribution network, as shown in Figure 55. The peak load, at around 50MW, falls between 13:00 and 14:00, lagging the plug-in times and a load of 15-20MW remains during the evening peak period.

Figure 55 – Predicted unmanaged load from national Royal Mail fleet

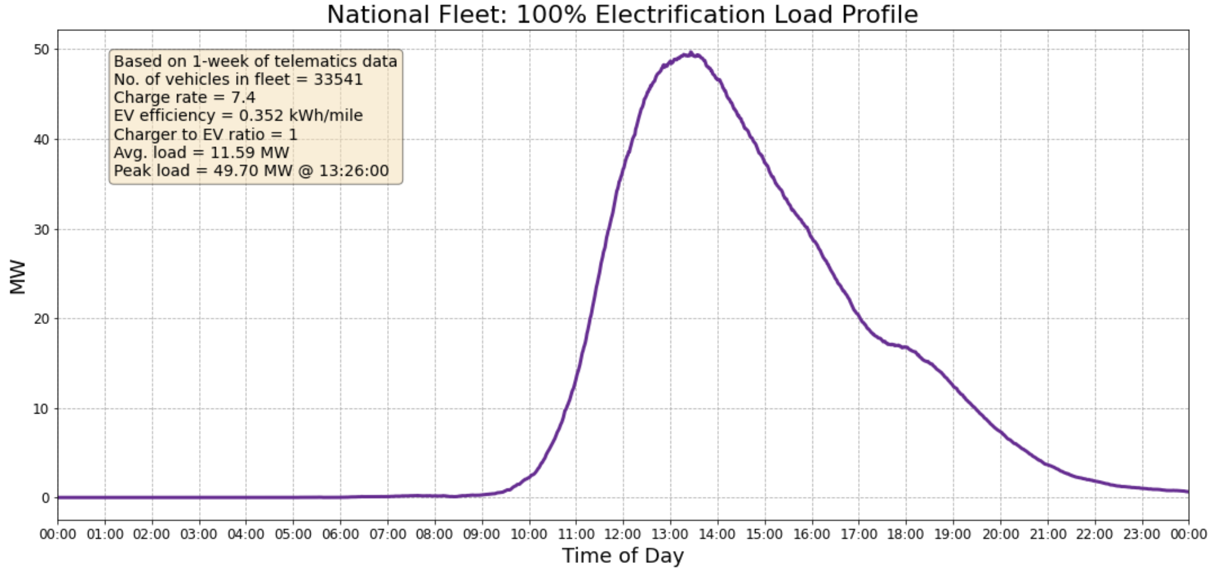
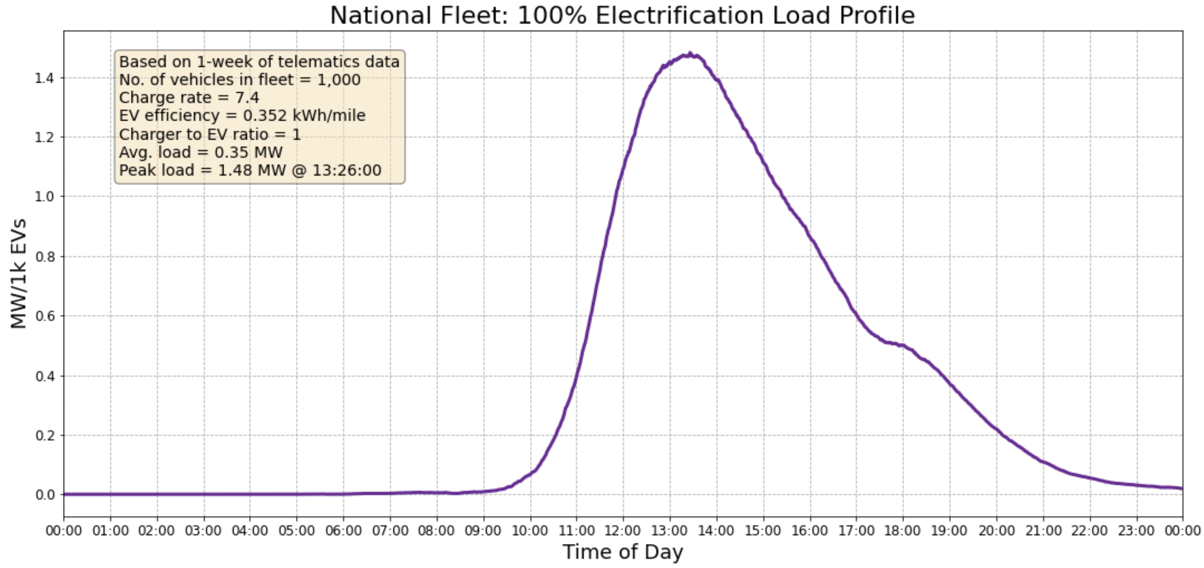


Figure 56 normalises this data to give the load per 1,000 vehicles. This results in a peak of over 1.4MW between 13:00 and 14:00 and load of 500kW between 17:00 and 18:00.

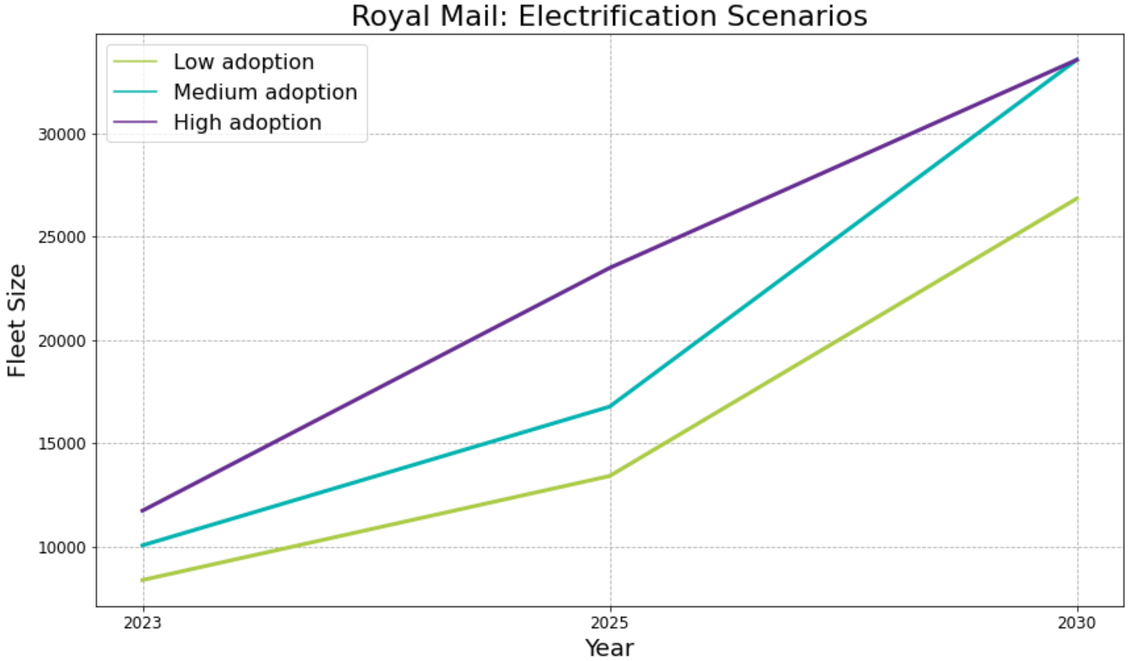
Figure 56 – Royal Mail national fleet unmanaged charging, normalised to 1,000 EVs



2.4.3 Growth scenarios for the EV fleet

Three fleet growth scenarios have been considered for the Royal Mail fleet, in line with those of British Gas – a high adoption scenario where electrification is relatively consistent up to the 2030 target; a medium scenario, where supply issues limit initial adoption (this is accelerated from 2025 to meet the target); a low adoption scenario, where fleet transition accelerates, but full electrification is not achieved by 2030. These scenarios are shown in Figure 57.

Figure 57 – Royal Mail Electrification Scenarios



The impact of these growth scenarios on maximum unmanaged load and on volume of electricity consumed can be found in Figure 58 and Figure 59 respectively.

Figure 58 – Forecasted unmanaged peak load from Royal Mail EVs

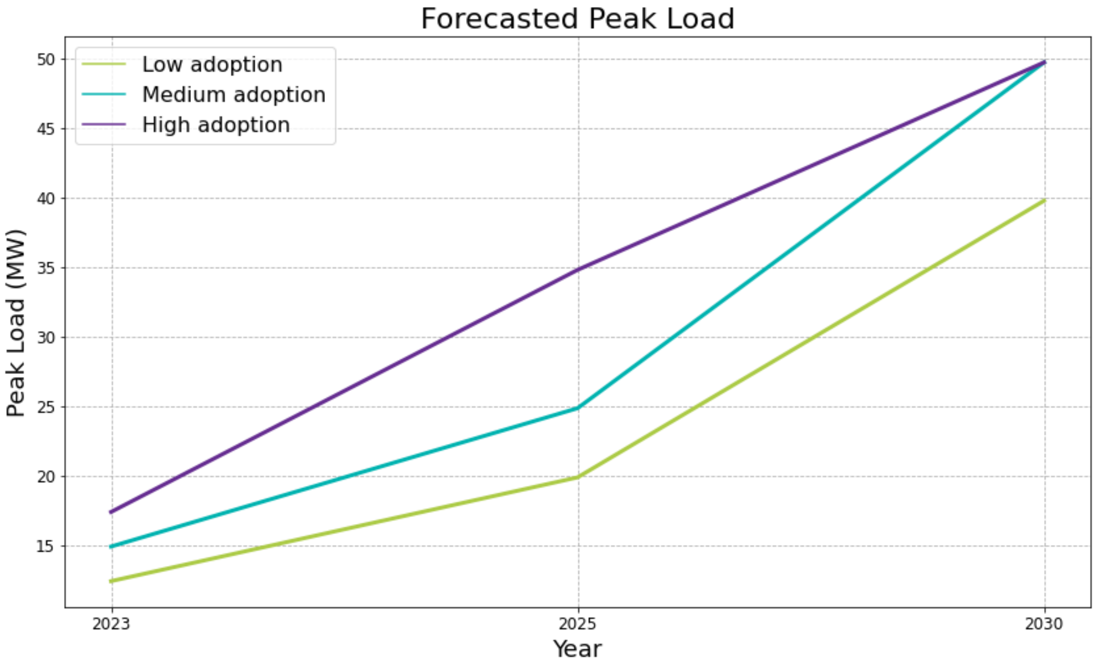
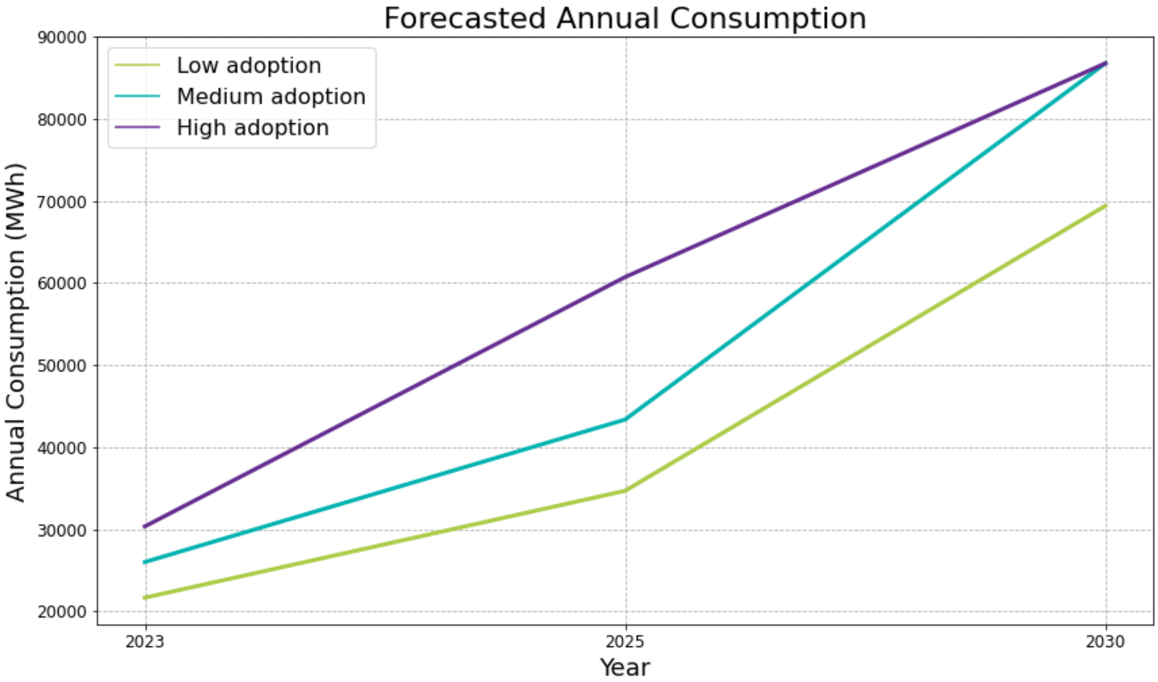


Figure 59 – Forecasted power consumption from Royal Mail EVs



3 WS3 – Mixed trial

The mixed trials analysed trip data from Uber PHVs to predict future impact on the distribution network and infrastructure requirements.

3.1 Data collected

The mixed trials collected and analysed anonymised trip data made available by Uber, detailing the trips undertaken by EVs on their platform in the Greater London area. This data included the time and location at each change in trip status (e.g. when the driver went from being available, to enroute to a customer, to on an Uber trip and back to available). In addition, Uber provided vehicle model data for each EV. The analysis in this section is based on 13 months of data from May 2021 to May 2022 inclusive.

The Uber data used in WS3 differs from WS1 and 2 in that the project only receives data on trips made by the vehicles, and not data on where and when the EVs charged. In order to calculate potential impact on the distribution network and issues with the current availability of charging infrastructure, it was necessary therefore to infer charging activity based on the data available. Full details on this methodology can be found in Deliverable D4 section 4.4.

3.2 Operational and Load profile analysis

Based on the trip and inferred charging data, Optimise Prime has analysed the usage patterns of the WS3 EVs. Deliverable D4, Section 4 presented an initial view of EV behaviour and this section gives and updated analysis based on the data collected throughout the trials. Since the initial analysis there have been a number of changes including the growth in the number of Uber EVs (from fewer than 500 at the start of the trials to over 6,000 in June 2022), an increase in the number of public CPs in Greater London (as shown in Figure 60) and an increase in the average battery capacity of the EVs (as shown in Figure 61). The period of study has also covered a period during which the COVID-19 pandemic had a significant impact on people’s mobility.

Figure 60 – Growth of EV charging infrastructure in Greater London (data provided by ZapMap)

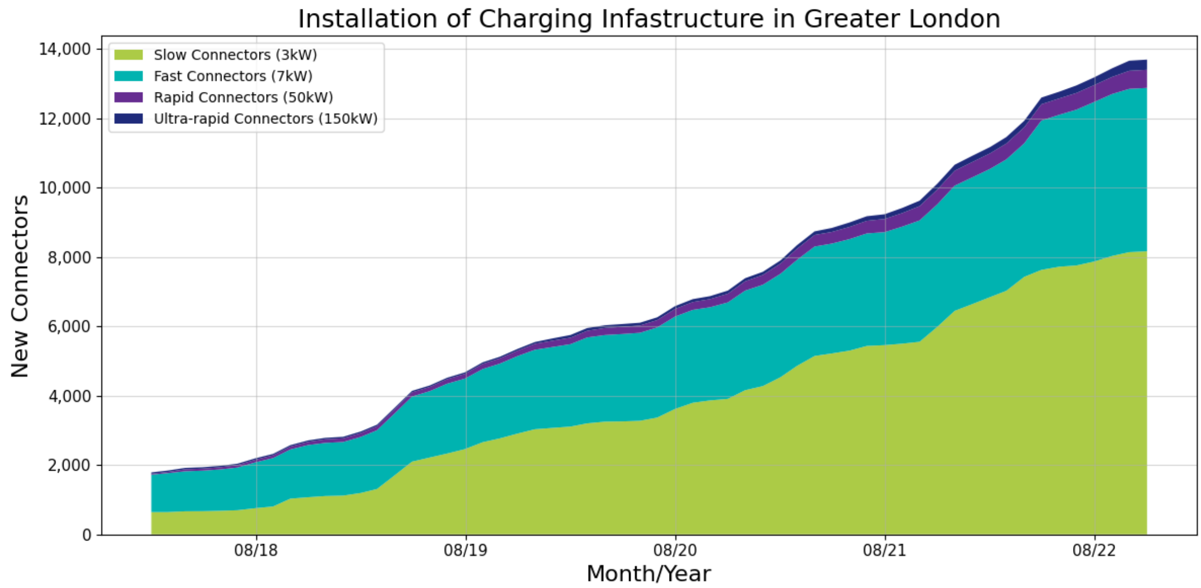
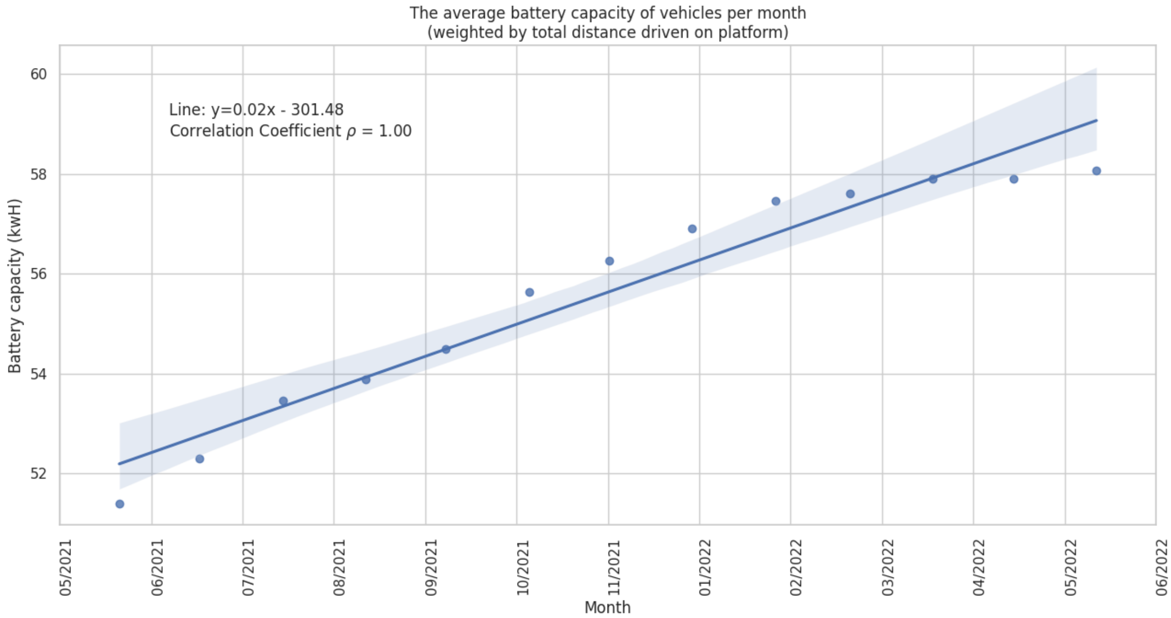


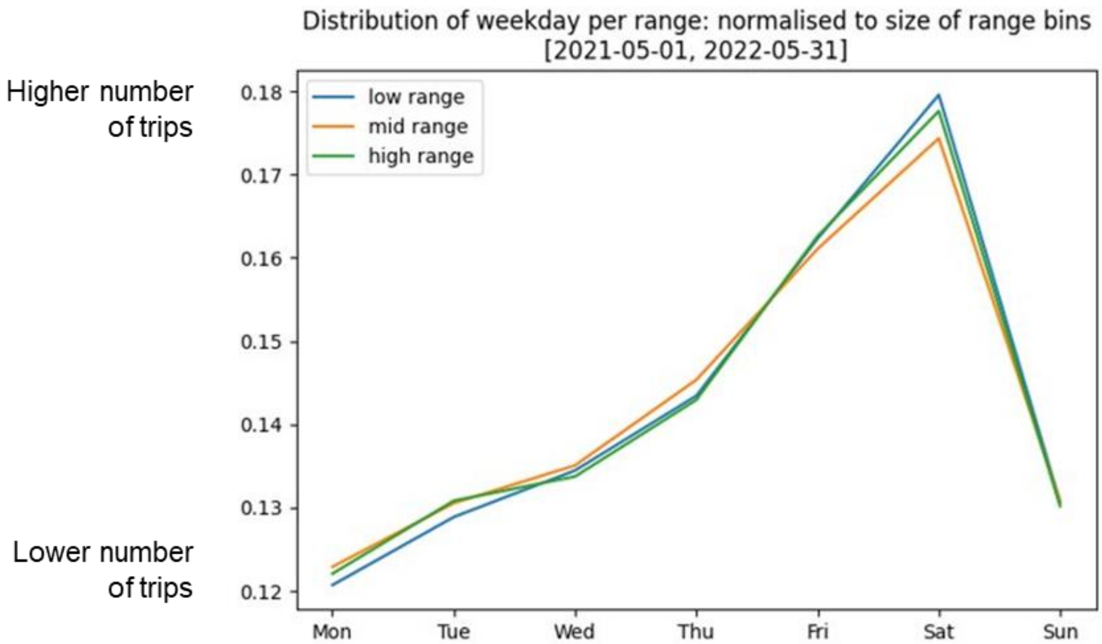
Figure 61 – Increase in average battery capacity of EVs on the Uber platform in London



Despite these changes, the key patterns seen in the analysis have been relatively stable.

Journey volumes vary throughout the week, from a low point on Monday to a peak on Saturday, when there are 50% more journeys taking place, as shown in Figure 62. Whereas in the early data high-range vehicles were less likely to operate at weekends, the latest data shows that vehicles of all ranges are equally likely to operate on each day of the week. It was found that lower range vehicles are slightly less likely to undertake some longer trips, such as trips to airports.

Figure 62 – Distribution of journeys throughout the week



As detailed in [Deliverable D4](), the project has found that trip data can be used to reasonably infer charging behaviour.

Averaged over all boroughs, the peak in electricity demand for Uber EV charging is at 20:00

3.2.1 On-shift charging

On-shift charging is where drivers charge in a break in their schedule during the day. Optimise Prime has found that Uber EV demand for on-shift charging activity is most intense in and around Central London. Heathrow airport is the only other location in the top ten most used CPs for on-shift charging. Table 9 shows the CPs in Greater London with the highest demand.

Table 9 – Most heavily utilised CPs, on-shift, May 2021-May 2022

LSOA	Location	Devices	Demand (charging events May 21 - May 22)	Average Charge events per day	No. Other rapid/ultra within 1 km
Camden 021B	Euston Osnaburgh	1x Rapid	10,503	10.5	0
Westminster 018C	St James	1x Rapid	9,141	13.6	1
Westminster 019C	Park Lane	11x Rapid	8,087	11.8	1
Southwark 002B	Borough Market / Southwark St	1x Rapid	7,297	11.8	0
Tower Hamlets 015D	Whitechapel	1x Rapid	7,265	12.2	0
Southwark 009F	New Kent Road	1x Rapid	6,437	11.2	0
Hillingdon 032A	Heathrow/ Bath Road	7x Ultra-rapid	5,963	26.6	1
Westminster 012A	Marylebone/Portman Sq	1x Rapid	5,834	10.7	10
Westminster 016B	Lancaster Gate	1x Rapid	4,248	10.1	1
Kensington & Chelsea 012C	Sloane Square	1x Rapid	4,028	8.5	2

As the CPs that were used by any particular driver were not known the modelling carried out assigned drivers to the most optimal public CP for their journey. The graphs in Figure 63 show that for these most popular CPs it is not unusual for maximum demand to exceed 100%, and sometimes the average demand will exceed 100%. As it is not possible for this demand to be satisfied, drivers must be making use of sub-optimal charging locations and additional infrastructure is likely needed in these central areas.

Figure 63 – Mean and maximum demand of the two most heavily used CP locations

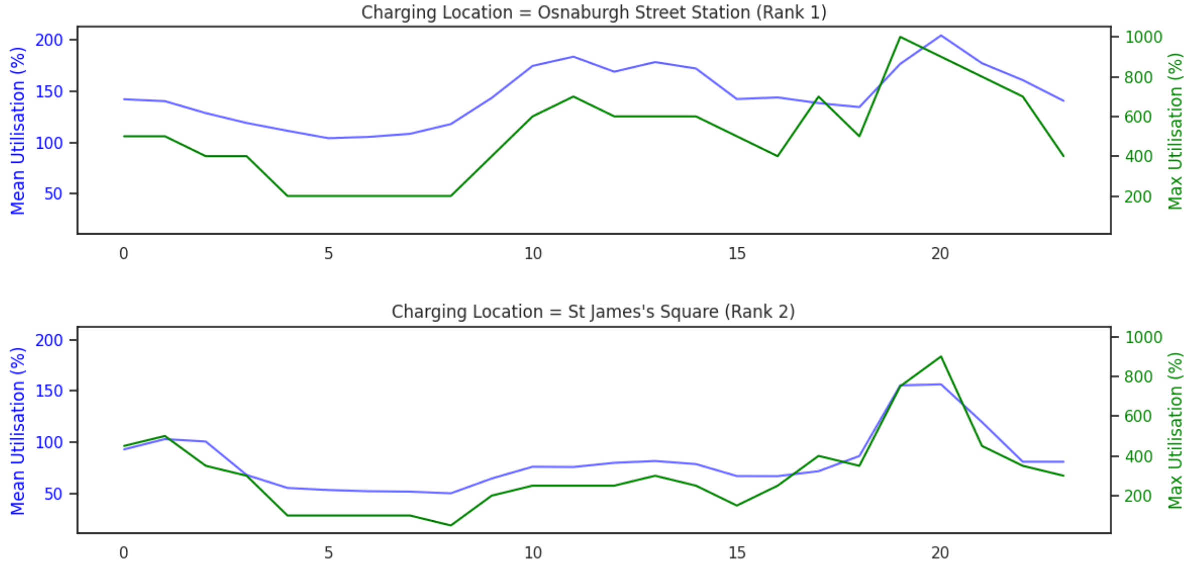
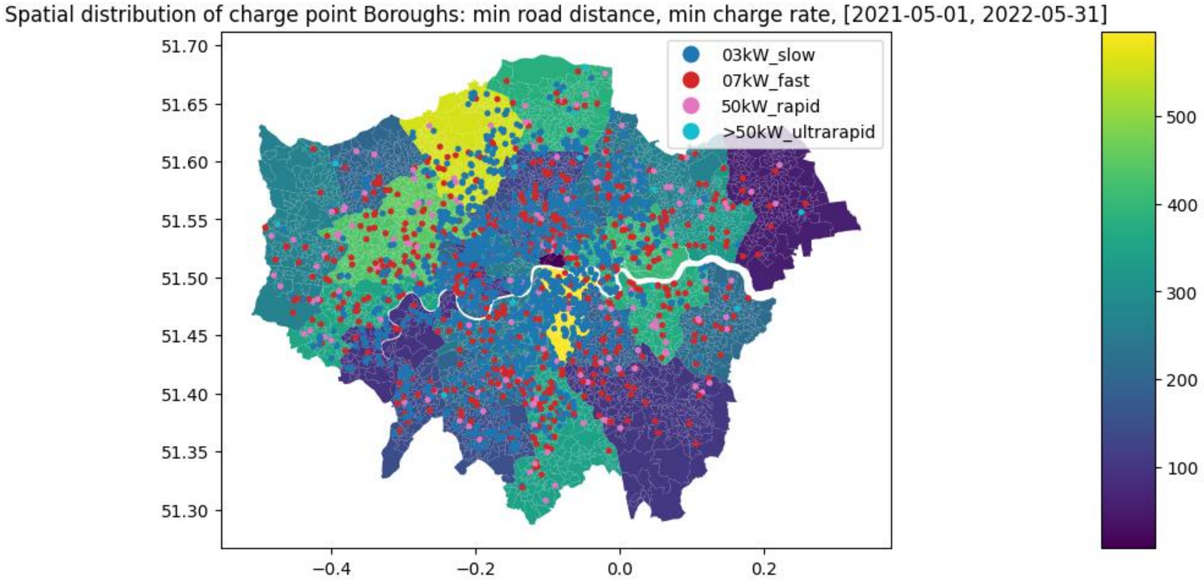


Figure 63 also shows the load shapes seen throughout the day from on-shift charging. This varies across different charging locations, though peaks are generally seen in the early afternoon and at around 20:00 in the evening.

3.2.2 Off-shift charging

Off shift charging – where a driver charges at the beginning or end of their shift, likely near their home, is the predominant method of charging Uber vehicles. Off-shift charge events occur throughout Greater London, as shown in Figure 64.

Figure 64 – Distribution of off-shift charge events throughout Greater London



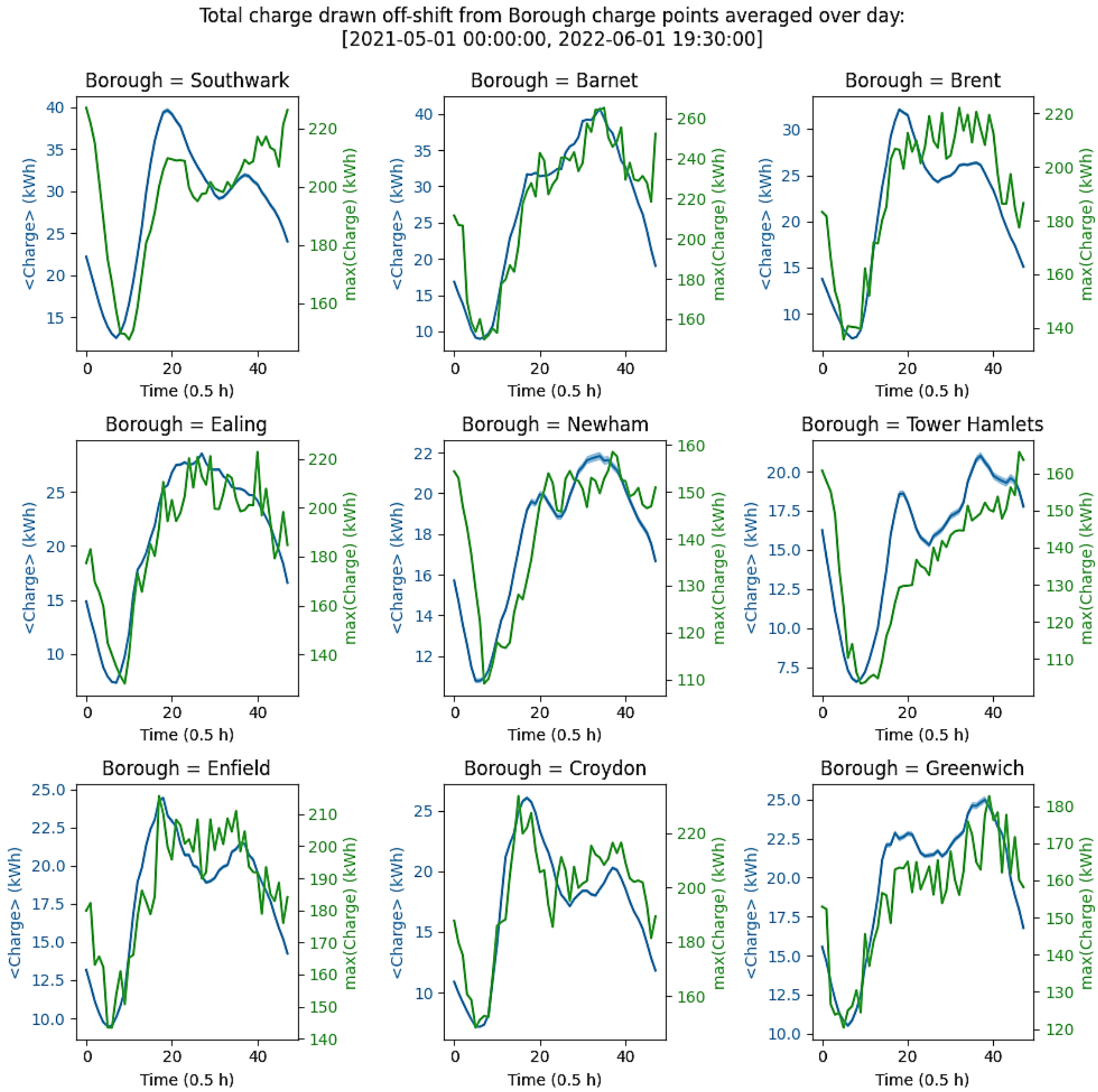
Because off shift drivers who rely upon public charging don't need to use rapid CPs, they have more choice of charging locations. The vehicles modelled travelled a median distance of 0.6km to get to a CP, however some areas on the edges of London can involve significantly longer journeys, some in excess of 5km if home charging is not available.

How this charging activity breaks down in terms of type of CP used in the top 10 boroughs for off-shift charging can be seen in Table 10. Public charging is primarily modelled to use slow and fast CPs closer to driver homes, as there is generally sufficient time between shifts for slow charging to take place. Section 3.3 will explore how the top boroughs are expected to change in the future as more drivers electrify.

Table 10 – Breakdown of off-shift charging events in top 10 boroughs, with breakdown of predicted CP type used

Ranking of borough by number of off-shift charge events	Home borough (regardless of where charging happens)	Public charging events by CP type			Home charging events in borough	Borough average off-street parking access (%)
		Slow	Fast	Rapid		
1	Barnet	26%	8%	3%	63%	59%
2	Southwark	87%	4%	0%	9%	19%
3	Ealing	30%	8%	2%	60%	56%
4	Croydon	25%	24%	3%	48%	55%
5	Lambeth	64%	5%	2%	29%	27%
6	Brent	56%	6%	1%	37%	55%
7	Newham	49%	26%	1%	24%	26%
8	Hounslow	49%	5%	2%	44%	56%
9	Enfield	25%	5%	6%	64%	58%
10	Tower Hamlets	63%	31%	1%	6%	8%

Figure 65 – Average and maximum daily load patterns in selected boroughs for off-shift demand



The patterns of load in selected boroughs can be seen in Figure 65. The blue line represents average demand throughout the day and the green line represents maximum modelled demand throughout the study period for each time period. The timing of the off-shift demand varies by borough, with most boroughs seeing an evening peak at around 20:00, and some boroughs also having an early afternoon peak as drivers working in the morning return home.

3.3 Future forecasts

While the number of EVs on the Uber platform in London has increased substantially over the course of the project (from less than 500 to in excess of 6,000), there is still further growth expected to occur in the coming years. Uber plan for 100% of their London PHVs to be EV by 2025. More broadly, Transport for London require all newly licenced PHVs to be Zero Emission Capable from 1 January 2023, accelerating the transition of the capital's approximately 83,000 PHVs to electric.

Optimise Prime has predicted how this fleet growth might impact upon demand for charging infrastructure and load on the distribution network. The forecast scenarios are based on Uber achieving 100% electrification in 2025.

3.3.1 Methodology

To create this future forecast, Optimise Prime has developed a forecasting methodology in order to infer how EV charging demand from Uber PHVs will develop as the electric fleet grows and develops.

This involves:

- Determining the home LSOA location of drivers
- Accounting for battery capacities increasing in the future by developing a battery capacity forecasting model
- Running the '*should charge*' model (S-model) to determine where, when and how much the drivers should charge
- Applying the outputs of the S-model analysis to the forecast of EV adoption for each borough
- Quantifying the associated energy demand
- Distributing new CPs in response to the additional energy demand
- Finding the optimal CP for each charging event
- Approximating the grid impact for on and off-shift charging

Several assumptions have to be made are made as part of the modelling. These assumptions align with the methodology used in the operational analysis.

- Vehicles begin each day with 80% charge and become more likely to charge as their battery SoC depletes. Drivers are also less likely to charge if there is a high demand for trips. These factors define whether they *should* charge.
- Drivers will only be able to charge during their shift if there is a sufficiently long break between trips, and a CP is close enough to get a minimum level of charge. These factors determine that they *could* charge. The should charge probability is used together with the could charge outcome to determine if drivers did charge.
- Drivers are allotted a home LSOA. It is presumed that home charging takes place in the same borough as their home LSOA.
- Battery capacities increase linearly between now and 2020, where they reach an average capacity of 80kWh (based on IEA Global EV Outlook predictions[3]). A distribution of battery capacities is used, based on current uptake, to reflect the fact that vehicles with varying ranges will be in use.
- The on-street vs. off street home charging split is informed by estimates of the proportion of homes with off-street parking in each borough. It should however be noted that anecdotal evidence suggests that PHV drivers are less likely to have off-street parking than the population as a whole.
- Potential CP speeds have been simplified for the purposed of the analysis. Table 11 shows the CP type categories used.

Table 11 – CP speeds used for forecasting

Charger Type	Power (kW)
Slow	3
Fast	7
Rapid	50
Ultra-rapid	150

- When deciding whether a new CP needs to be installed an assumption is made on how much of each CP's capacity can be used by Uber vehicles before an additional CP is required. This is necessary to consider the fact that Uber drivers will not be able to use

[3] https://iea.blob.core.windows.net/assets/af46e012-18c2-44d6-becd-bad21fa844fd/Global_EV_Outlook_2020.pdf

the CP continuously throughout the day, that there are some CPs Uber drivers will never use, and other drivers will also make use of the CPs. Table 12 shows the utilisation figure used for each CP type.

Table 12 – Assumed maximum Uber CP utilisation

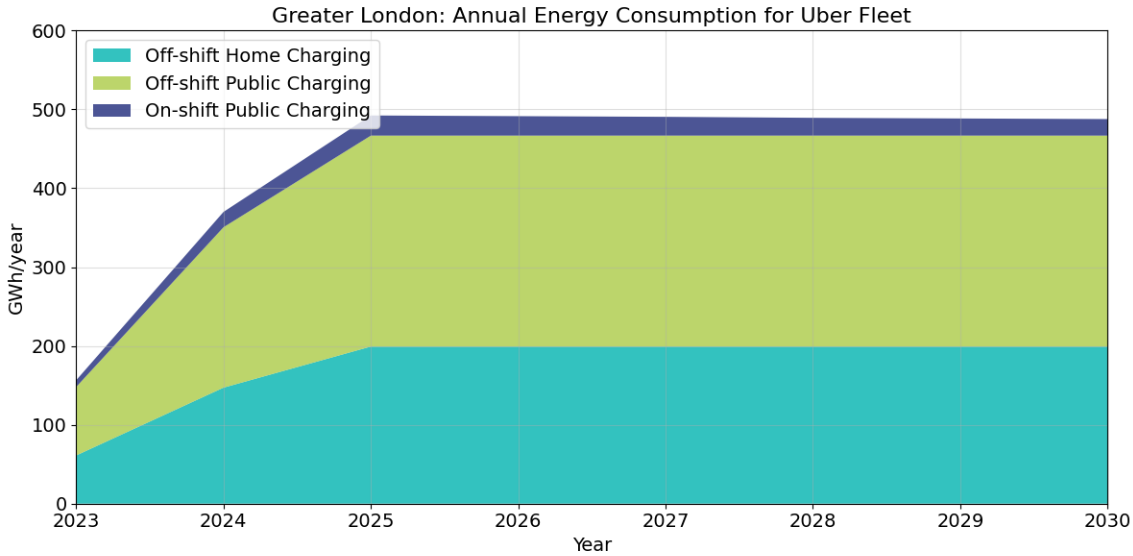
Charger Type	Uber Utilisation	Hours Occupancy/Week
Slow	15%	42 Hours
Fast	10%	16.8 Hours
Rapid	7.5%	12.6 Hours
Ultra-rapid	7.5%	12.6 Hours

3.3.2 Demand modelling

The energy demand estimate is calculated by calculating the mean energy demand in each LSOA per EV from each borough using the S-model methodology described above (More details of this model can be found in Deliverable D4).

Figure 66 shows the growth in total electricity demand from Uber EVs in Greater London. The rapid growth up to 2025 reflects Uber's target of a fully electrified fleet by 2025. On-Shift charging is expected to represent a small proportion of Uber charging activity (in 2023, 5.5% of total energy and 16% off charge sessions), with this proportion declining slowly over time (to 4% and 13% respectively by 2030) as more EVs can complete a full day without top-up charging. Throughout this analysis, 2023 and 2025 are used as the first and last years of the analysis due to the limited change between 2025 and 2030.

Figure 66 – Annual energy consumption from Uber PH EVs



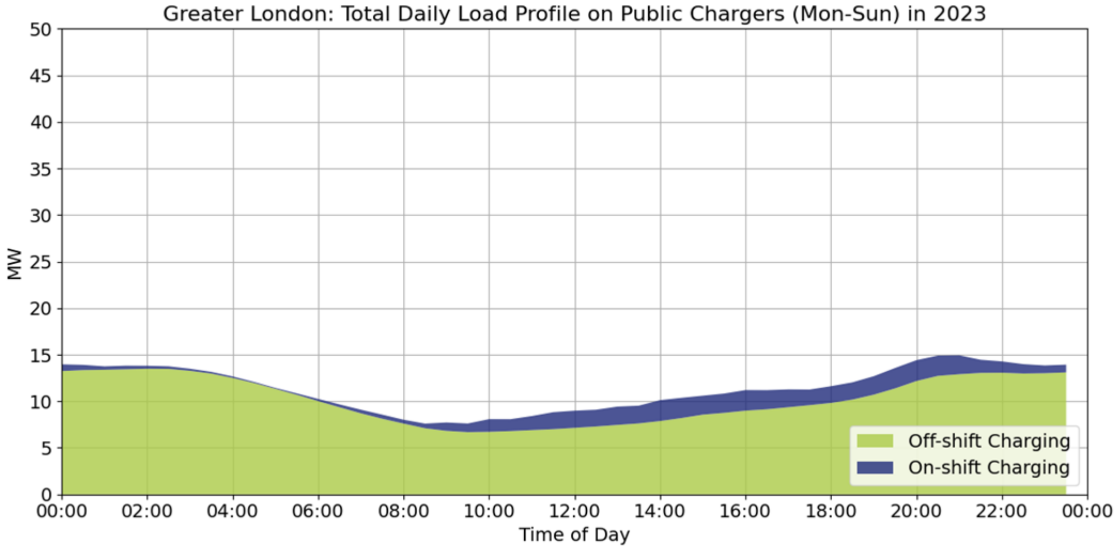
The estimated public charging demand, when scaled against the full PHV fleet, comes in at the low end of estimates in Transport for London's 2030 Electric Vehicle Infrastructure Strategy[4], potentially reflecting over estimation of the proportion of drivers who can charge off-street. The following analysis focuses on the on-street public charging infrastructure requirements.

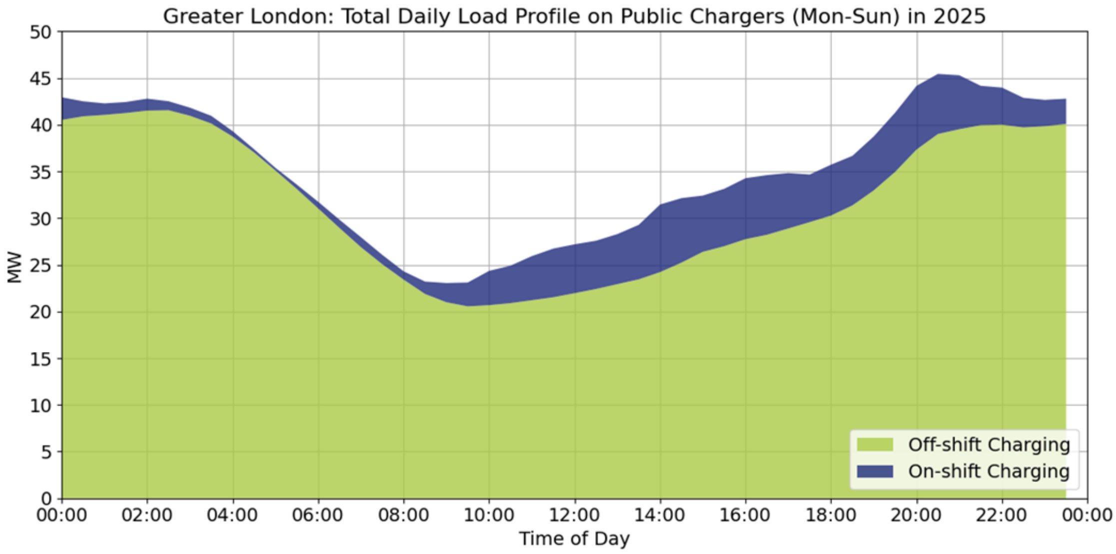
Across the day, load profiles on public chargers are expected to stay relatively consistent, but the magnitude of power used by the vehicles will increase, as shown in Figure 67. Off shift

[4] https://tfl.gov.uk/ruc-cdn/static/cms/documents/london-2030-electric-vehicle-infrastructure-strategy-december-2021.docx

load is highest from 20:00 to 04:00 and peaks around 02:00 when the highest numbers of vehicles are plugged in and charging – the peak is 231% higher in 2030 vs 2023. On shift load peaks around 14:00 in the afternoon and again at around 20:00 – the peak is 160% higher in 2030 vs 2023.

Figure 67 – Uber load on public CPs 2023 (above) vs 2025 (below)





Demand for public chargers will not be uniform throughout the city and will change over time as more drivers electrify. Table 13 shows the predicted top five boroughs for on and off shift charging volumes in 2023 and 2030.

Table 13 – Public charging demand, top five boroughs

Rank	2023		2025	
	On-shift	**Off-shift**	**On-shift**	**Off-shift**
1	Hillingdon	Tower Hamlets	Hillingdon	Tower Hamlets
2	Westminster	Newham	Westminster	Newham
3	Lambeth	Southwark	Tower Hamlets	Brent
4	Tower Hamlets	Lambeth	Lambeth	Barnet
5	Camden	Wandsworth	Brent	Ealing

3.3.3 Modelling the need for new CPs

The utilisation of existing public CPs varies. Some have more demand than they accommodate, while others are underused, as they do not currently serve Uber EV drivers. Figure 68 shows how the number of public CPs has increased in recent years, increasing by around 50% each year.

Figure 68 – EV charger growth in Greater London, by type

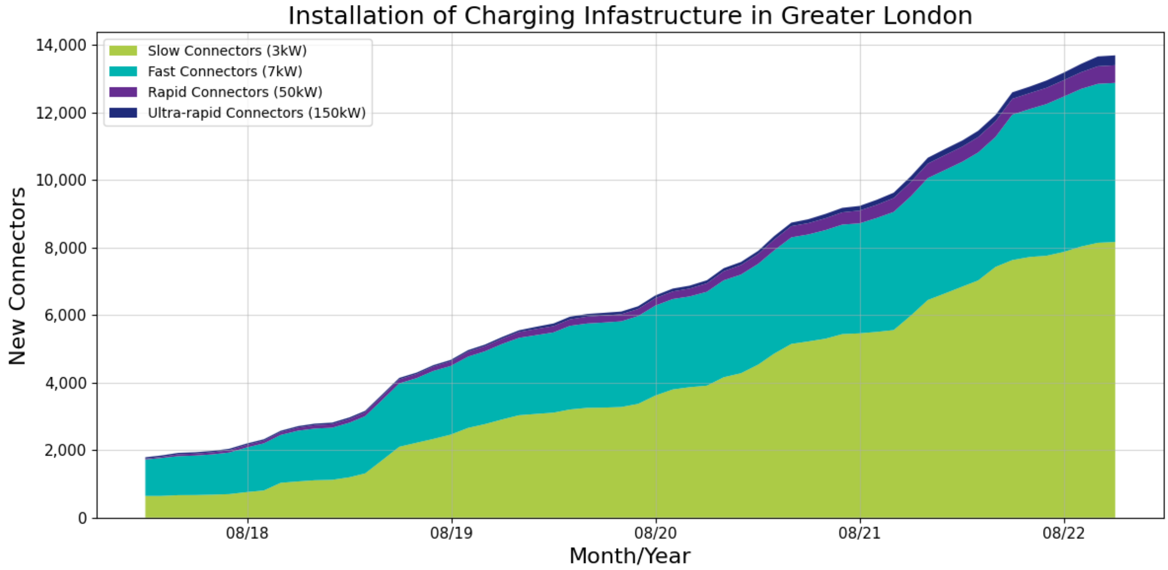
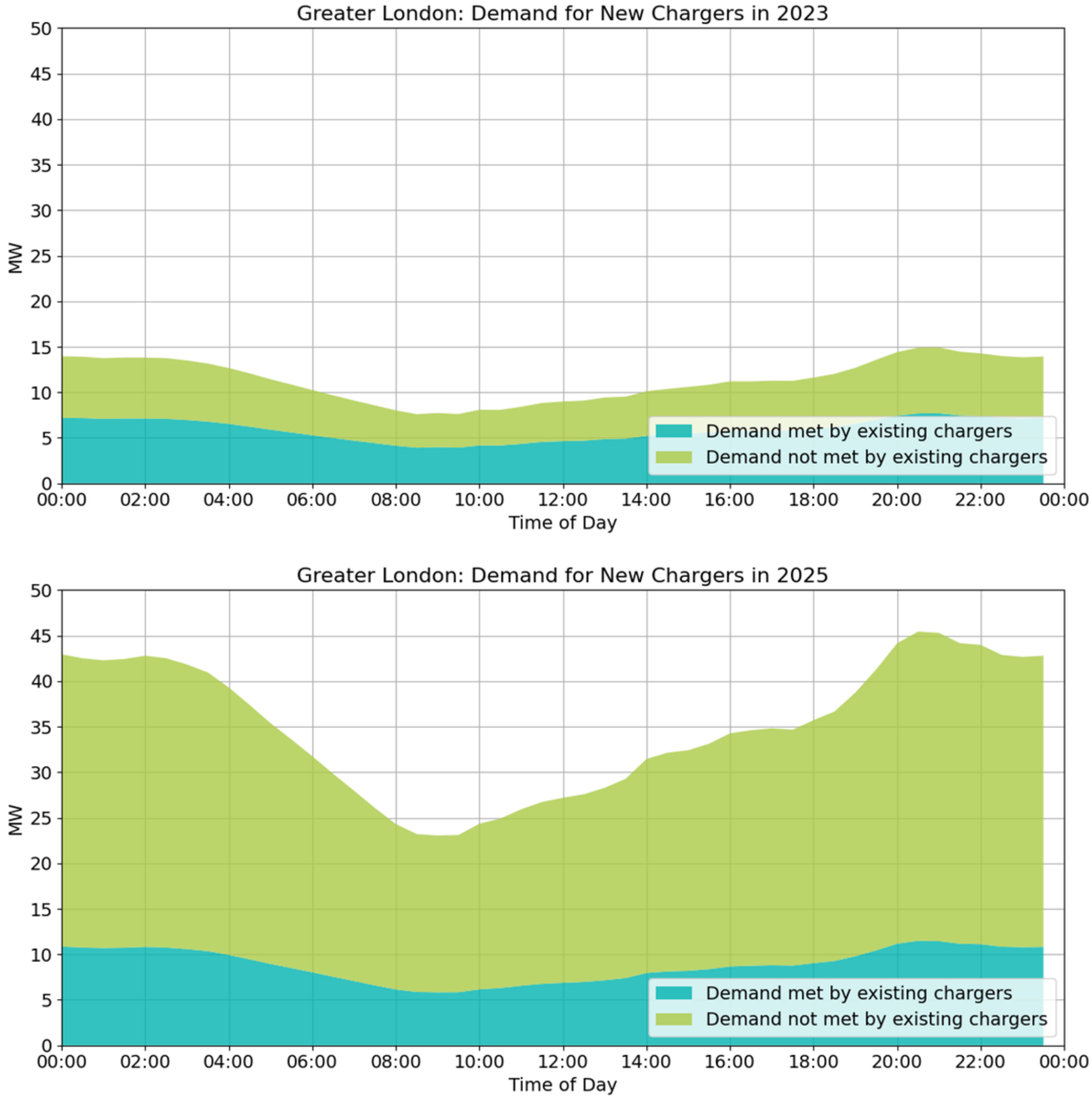


Figure 69 shows the proportion of Uber demand that can be met by the current CP estate in future years. Additional demand will require the installation of new chargers if drivers are to charge optimally.

Figure 69 – Ability of existing public CPs to meet forecast demand 2023 (above) and 2025 (below)



In modelling the demand for CPs, two scenarios have been created:

- Scenario 1 – Ultra-Rapid CPs are prioritised for on-shift charging, Fast CPs are prioritised for Off-shift charging.
- Scenario 2 – Ultra-Rapid CPs are prioritised for all charging.

Installations of ultra-rapid CPs is outpacing rapid CPs and they are likely to be chosen by Uber drivers in the future given the potential opportunity cost of on-shift charging. For off-shift charging, these two scenarios are seen as the two extreme future scenarios – either drivers use on-street fast chargers outside their homes, or they use ultra-fast hubs in their home borough. In reality it is likely that drivers will use a mix of these models, depending on how the infrastructure is developed.

In both scenarios, slow and rapid CPs will be specified if demand is not sufficient to require a fast or ultra-rapid CP.

3.3.3.1 Scenario 1

In the fast-charging dominant scenario, it is anticipated that 38,249 fast public CPs will be needed in Greater London to satisfy demand from Uber drivers, 466 ultra-rapid CPs will be required for on-shift charging, as shown in Table 14.

Table 14 – CPs required in 2025, Scenario 1

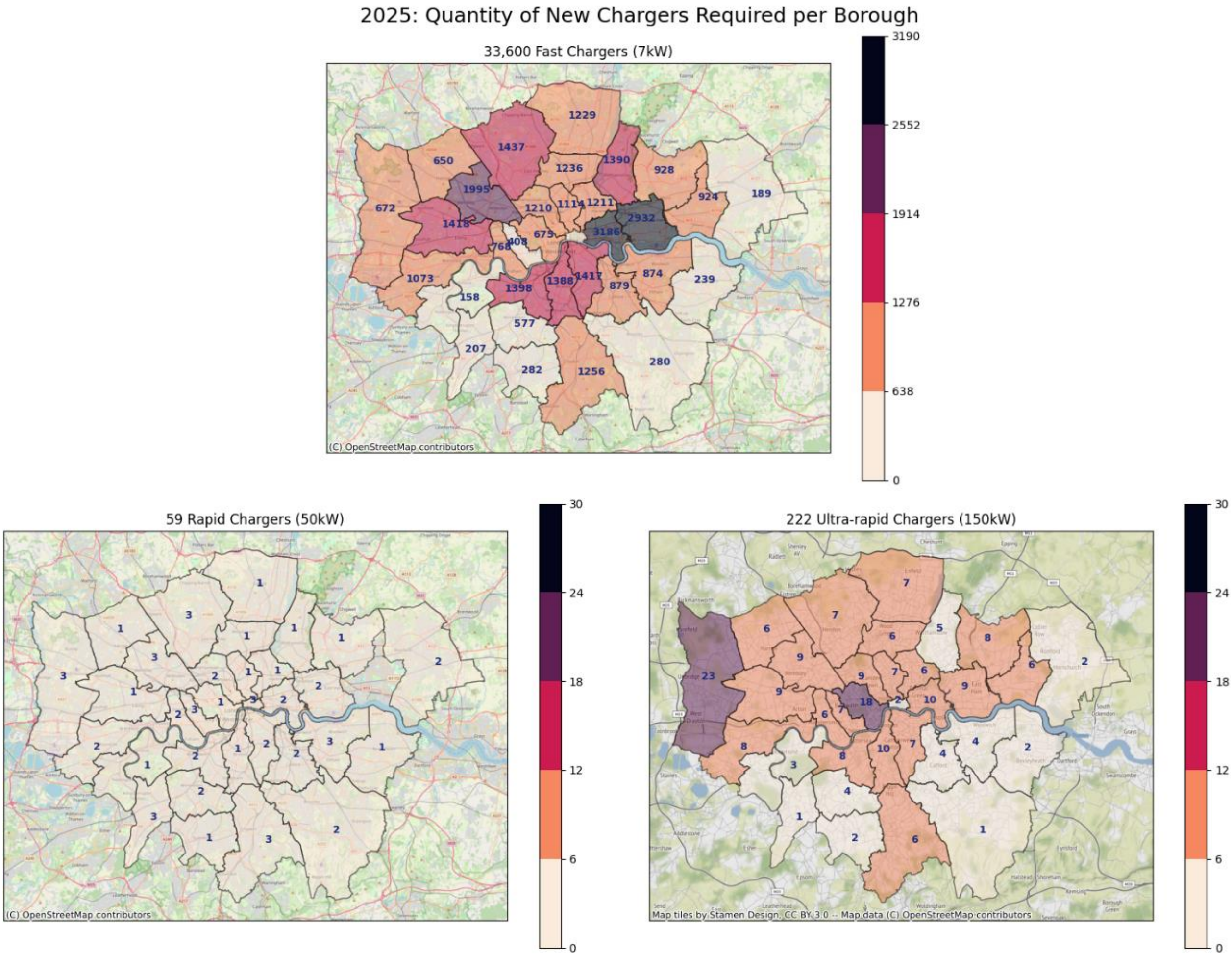
Charger Type	No. of Additional Connectors Required	Existing No. of Chargers	Total No. of Public Chargers
Slow	47	8,163	8,210
Fast	33,600	4,710	38,310
Rapid	59	523	582
Ultra-rapid	222	293	515

The geographic location of additional chargers in shown in Figure 70. Requirements for fast CPs is focussed in areas where Uber drivers are more likely to live, with hotspots in Tower Hamlets, Newham and Brent. Demand for ultra-rapid CPs is focused on areas surrounding destinations such as Central London boroughs and Heathrow Airport, in addition to the residential hotspots. Table 15 shows how, over time, the requirement for CPs changes from more central to more residential locations.

Table 15 – CP requirement of top five boroughs, 2023 and 2025, Scenario 1

2023			2025		
Borough	**New CPs required**	**Capacity of new CPs (MW)**	**Borough**	**New CPs required**	**Capacity of new CPs (MW)**
Tower Hamlets	599	4.5	Tower Hamlets	3,200	23.9
Southwark	460	3.5	Newham	2,944	22
Newham	467	3.5	Brent	2,009	15.5
Lambeth	410	3.2	Barnet	1,448	11.3
Westminster	318	2.8	Ealing	1,429	11.3

Figure 70 – Forecast requirement for additional CPs, 2025, Scenario 1



3.3.3.2 Scenario 2

In Scenario 2, where all drivers prefer to use ultra-rapid CPs, 2,311 new ultra-rapid CPs are required by 2025 – 2,089 more than in Scenario 1 – in addition to 62 rapid CPs. The geographical spread of these CPs can be seen in Figure 71. As can be seen in Table 16, the boroughs with the highest demand in 2025 are those where Uber drivers are likely to live, including Tower Hamlets and Newham. The amount of capacity required for Scenario 2 is approximately 25% higher than in Scenario 1.

Figure 71 – Forecast requirement for additional CPs, 2025, Scenario 2

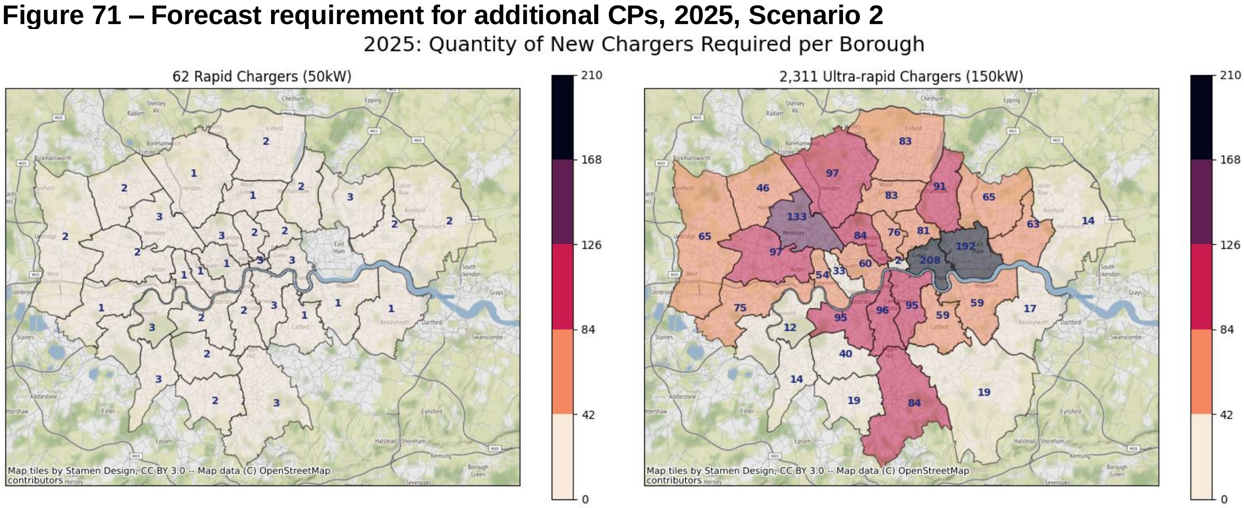


Table 16 – Forecast requirement for additional CPs – top 5 boroughs, 2025, Scenario 2

Borough	No. of Ultra-rapid Connectors	Capacity Required
Tower Hamlets	208	31.2 MW
Newham	192	28.8 MW
Brent	133	19.9 MW
Barnet	97	14.6 MW
Ealing	97	14.6 MW

3.3.4 Impact of the additional CP demand on the distribution network

Table 18 – 2025 CPs required and current substation headroom in top 5 boroughs, Scenario 1

Borough	CPs required by capacity				Capacity of new CPs (MW)	No. substations in borough		
	3 kW	7 kW	50 kW	150 kW		Green >=400kVA	Amber >=200, <400 kVA	Red <200kVA
Tower Hamlets	2	3,186	2	10	23.9	464	197	173
Newham	1	2,932	2	9	22	311	186	147
Brent	2	1,995	3	9	15.5	313	200	166
Barnet	1	1,437	3	7	11.3	367	260	138
Ealing	1	1,418	1	9	11.3	510	585	501

Figure 72 illustrates the current headroom (capacity – peak demand) of substations across the Greater London area. Areas marked in red indicate areas where there is less than 200kVA capacity available on local substations, on average, and installation of ultra-fast CPs may require new transformers to be added. Table 17 lists the five boroughs with the most constrained substations, these are primarily boroughs of outer London.

Table 17 – Five boroughs with most constrained substations

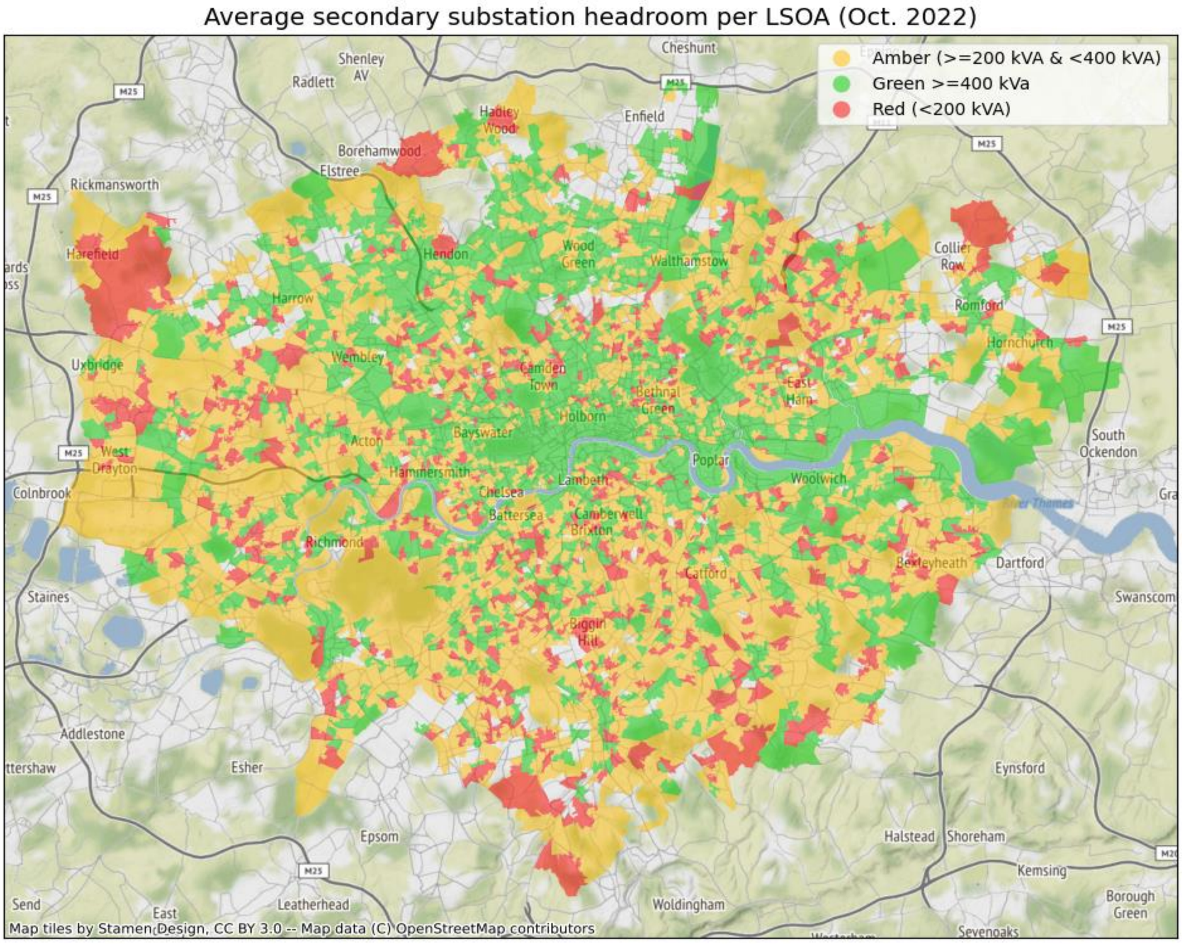
Borough	% of Substations <200 kVA Headroom
Sutton	37%
Croydon	34%
Hillingdon	33%
Bromley	32%
Ealing	31%

Table 18 gives a comparison of the 2025 CP requirements of the top five boroughs in Scenario 1, compared to the current headroom of substations in the borough, which is further visualised in Figure 72. On an aggregate level, there is sufficient capacity across the borough to install the required number of CPs – the additional CPs require between 5.3% and 7.7% of the available headroom in these boroughs. However, availability of capacity is location specific and there are a significant number of locations with lower levels of capacity. The availability of capacity may not always align with locations that are both convenient for Uber drivers and where it is physically possible to install a CP. Available capacity is also likely to diminish over time as more customers connect to the network.

Table 18 – 2025 CPs required and current substation headroom in top 5 boroughs, Scenario 1

Borough	CPs required by capacity				Capacity of new CPs (MW)	No. substations in borough		
	3 kW	7 kW	50 kW	150 kW		Green >=400kVA	Amber >=200, <400 kVA	Red <200kVA
Tower Hamlets	2	3,186	2	10	23.9	464	197	173
Newham	1	2,932	2	9	22	311	186	147
Brent	2	1,995	3	9	15.5	313	200	166
Barnet	1	1,437	3	7	11.3	367	260	138
Ealing	1	1,418	1	9	11.3	510	585	501

Figure 72 – Substation headroom on the distribution network in London



3.3.5 Feasibility of installing CPs at specific locations on the distribution network

Overall, there is generally sufficient capacity on the network to meet the future charging needs of Uber PHVs. Even in the top five boroughs for CP growth, the additional load will be equivalent to between 5.3% and 7.7% of available headroom on secondary substations. However, as shown in Section 3.3.4, ability of individual substations to take additional load does vary substantially. Limitations on charging are also likely to be the result of other considerations, such as space, physical ability to connect in specific locations and ability to connect multiple chargers in the same location.

In order consider cost to the charge point operator of installing the necessary CPs, the UK Power Networks connections team carried out a feasibility study on 30 potential sites in the London Borough of Newham for on street fast CPs serving off-shift demand and 20 sites, mainly in Central London, for rapid/ultra-rapid CPs to serve on-shift demand.

Of the 30 locations in Newham, 27 were located on the same side of the road as an LV main and would require minimal work by the DNO and a connection cost of approximately £2,500 per site, accommodating up to three 7.4kW CPs. The remaining three potentially required additional cables to be installed increasing costs to up to £10,000. It should be noted that in less urban areas the network may be less dense, resulting in more locations where there is not an LV main on both sides of the road.

Of the 20 sites selected for on-shift CPs, seven were capable of supplying an ultra-rapid CP from existing transformers. Ten could only support rapid CPs (although sometimes in multiple if split among different points of connection. At the remaining locations a suitable site for a CP could not be found. DNO costs generally ranged from £10,000 to £30,000 per location.

Drivers may prefer sites with multiple CPs to reduce the need to queue – any site requiring multiple ultra-rapid CPs, such as a hub would likely require a new dedicated transformer. This highlights the potential additional cost of installing ultra-rapid infrastructure in areas, such as Central London, that in aggregate have sufficient capacity.

3.3.6 Key findings from future forecasts

- Increased electrification of Uber's PHVs will cause rapid growth in both on and off-shift energy demand across Greater London until 2025, with a total annual demand of 495 GWh for the Uber fleet forecast from 63 GWh in June 2022
- On-shift charging peak loads are at 14:30 and 20:00 reaching a maximum load of 6MW in 2030. This is compared to a 2.2MW peak load at 20:30 in 2022
- Off-shift charging peak loads are at 02:30 with a maximum load of 69MW in 2030. In 2022 there is a 8.3MW peak load at 01:00 with a secondary peak of 8.2MW at 21:00
- A likely scenario involves PHV drivers utilising 7kW on-street CPs when not working and ultra-rapid 150kW CPs to recharge during their shifts. In this case, 33,928 additional CPs would be needed in London by 2025 to meet Uber drivers' demand for public charging infrastructure
- If 150kW CPs were to be used for all public charging, only 2,373 additional CPs would be needed, but they would require 25% more capacity than the likely scenario described above
- The distribution network as a whole currently has capacity to meet these demands, however localised constraints may require upgrades to be made. Suburban areas with low access to off-street parking are likely to have particularly high demand for public charging infrastructure, whether this is in the form of on street fast CPs or ultra-rapid hubs.
- Demand for this infrastructure is likely to develop quickly as the PHV sector is one of the first to fully electrify, driven by regulatory pressures. DNOs will need to work closely with CP operators to ensure that sufficient capacity is put in the right places to meet this demand.