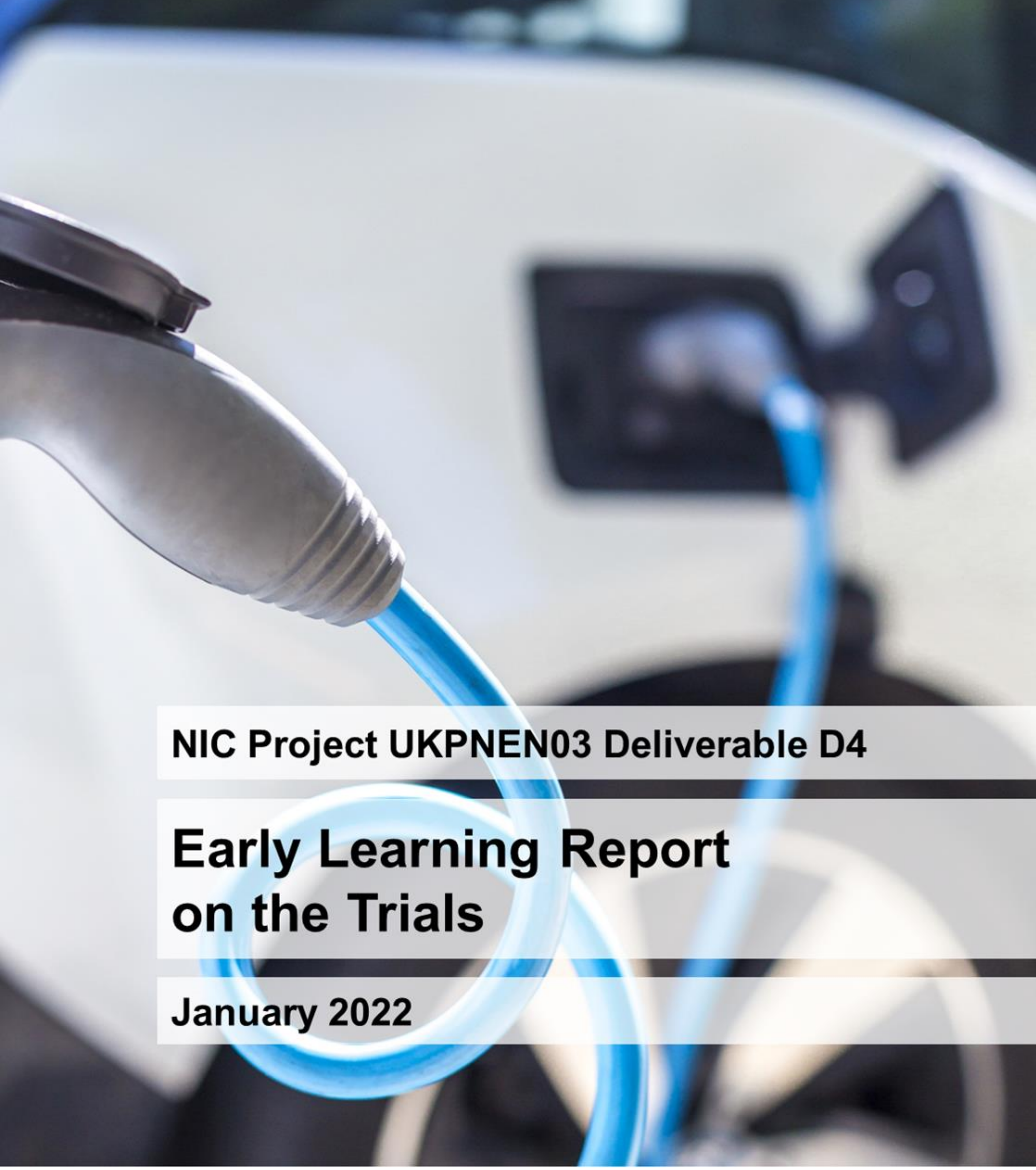

NIC Project UKPNEN03 Deliverable D4

Early Learning Report on the Trials

January 2022

Optimise Prime

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

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Table of acronyms & glossary

The acronyms and terms used throughout this document are clarified below.

Table 1 – Table of acronyms

Acronym	Full form
ANM	Active Network Management
AOI	Area of Interest
API	Application Programming Interface
ASC	Authorised Supply Capacity
BAU	Business As Usual
CP	Charge Point
CSMS	Charge Station Management System
DC	Direct Current
DNO	Distribution Network Operator
DSO	Distribution System Operator
EPN	Eastern Power Networks plc
EV	Electric Vehicle
FSP	Full Submission Pro-forma (in reference to the project proposal)
FU	Flexible Unit
GB	Great Britain
hm	Hectometre (100 metres)
HV	High Voltage
ICE(V)	Internal Combustion Engine (Vehicle)
IT	Information Technology
kW	Kilowatt
kWh	Kilowatt hour
LAD	Local Authority District
LPN	London Power Networks plc
LSOA	Lower Layer Super Output Area
LV	Low Voltage
MWh	Megawatt hour
MSOA	Middle Layer Super Output Area
NIC	Network Innovation Competition
OTA	Over-the-Air
PH(V)	Private Hire (Vehicle)
PTU	Programme Time Unit
RAG	Red-Amber-Green
RFID	Radio-Frequency Identification
SoC	State of Charge
SPN	South Eastern Power Networks plc
SSEN	Scottish & Southern Electricity Networks
TCO	Total Cost of Ownership
TfL	Transport for London
UUID	Universally Unique Identifier
UK	United Kingdom
VIN	Vehicle Identification Number
W(h)	Watt (hour)
WS	Workstream

Table 2 – Glossary of terms

Term	Definition
Un-managed charging	Charging of an EV at the rate set by the connection until it reaches full charge or is disconnected.
Smart charging	Charging via a smart charger equipped with two-way communication, enabling charging habits to be adaptive.
Flexibility	The ability to respond dynamically to a signal provided by the DNO to increase or decrease the power exchanged with the network, compared to an initial planned behaviour. In Optimise Prime there are three flexibility products: Product A – Firm Forward Option; Product B – Spot Market; Product C – Balancing Market.

Executive summary

Optimise Prime is a third-party industry-led electric vehicle (EV) innovation and demonstration project that brings together partners from leading technology, energy, transport and financing organisations, including Hitachi Vantara, UK Power Networks, Centrica, Royal Mail, Uber, Scottish & Southern Electricity Networks, Hitachi Europe and Hitachi Capital Vehicle Solutions.

The project is gathering data from over 3,000 EVs driven for commercial purposes through three trials. Optimise Prime will also implement a range of technical and commercial solutions with the aim of accelerating the transition to electric vehicles for commercial fleet operators, while helping GB's distribution networks plan and prepare for the mass adoption of EVs.

Through cross-industry collaboration and co-creation, the project aims to reduce the impact of EVs on distribution networks and ensure security of electricity supply while saving money for electricity customers, helping the UK meet its clean air and climate change objectives. The project consists of three trials – WS1, investigating the impact of commercial vehicles charging at Homes, WS2, monitoring and optimising commercial vehicles charging in depots and WS3, which uses private hire vehicle (PHV) journey data to model the impact of these vehicles on the distribution network. The trial period for WS3 began in August 2020, with WS1 and WS2 trials commencing on 1 July 2021. All trials are due to conclude in June 2022.

Optimise Prime's outcomes will include:

- Insight into the impact of the increasing number of commercial EVs being charged at domestic properties, and commercial solutions for managing home based charging
- A site planning tool and analysis of optimisation methodologies enabling an easier and more cost-effective transition to EVs for depot-based fleets
- A methodology for implementing profiled connections for EVs, implemented in coordination with network planning and active network management tools
- Learnings regarding how useful and commercially attractive flexibility services from commercial EVs can be to DNOs, and how such services could be implemented
- A significant dataset and accompanying analysis on the charging behaviour of commercial vehicles

This report forms the fourth Optimise Prime deliverable, D4, providing an interim overview of lessons learnt from conducting the trials, summarising the data collected, insights gained and required changes that have been identified during the pre-trial period and in the first months of trial activity. Over this time the project has collected and analysed data from a wide range of sources in order to carry out a wide range of experiments. These experiments will allow the project to test the efficacy of the Optimise Prime methods and model the potential impact of EV growth on distribution networks.

Some of the key insights and challenges, which are discussed in more detail throughout this report, include:

WS1 – Return-to-Home Trials

- Unmanaged, the peak charging demand from return-to-home vehicles is likely to occur between 17:00 and 19:00, coinciding with peak demand on the distribution network.

- Smart charging has been modelled to significantly reduce peak demand from return-to-home vehicles. However, the benefits of simply shifting load later are much less than of balancing load over a longer period.
- Within the return-to-home trial there is expected to be a significant seasonal variation in power demand, based on analysis of ICEV data. Future work will look at differentiating between seasonal variations between differences in British Gas workload and other factors.
- The majority of British Gas fleet journeys should be able to be fulfilled with the current generation of EV Vans. On-route charging could be used for occasional longer trips.

WS2 – Depot Trials

- Modelling has created predictions of charging demand in unmanaged and smart scenarios. These models demonstrate that smart charging should deliver reduction of peak demand for the networks as well as energy and connection cost savings for the depot operator.
- Initial trials and modelling of profiled connections have shown that it should be possible to utilise control of EV charging to keep sites within an agreed profile. However there may be some sites where there is too little controllable EV demand to do this reliably.
- Flexibility trials have shown an ability to control charging in response to flexibility requests from the Distribution Network Operator (DNO). With the forward option product a significant difference between forecast (month ahead) and actual demand has been encountered, so future trials will look at improving the reliability of forecasting.
- The reliability of using RFID (radio frequency identification) tags to accurately identify the vehicles that can be controlled continues to be an issue and can limit the availability of controllable load at depots. The project is looking at how this could be resolved through process changes.

WS3 – Mixed Trials

- The data from Uber trips has allowed the trials to model charging events and demand throughout Greater London. Charge demand from PHVs is likely to peak in the evening as some drivers return home and others need to top up.
- There is a clear pattern within and across days in trip and charging demand. Impact of weather on trip patterns appears to be limited.
- There is a significant number of locations where drivers need to travel far if they need to charge during their shift. These are most frequently found in the Central London borough of Westminster and the City of London, where there is limited availability of rapid chargers.
- Based on modelling the optimal CP for each charge event, the most popular CPs in London are utilised way beyond their capacity, suggesting drivers will have to queue in order to charge when they are at their busiest, or travel further in order to use non-optimal CPs.
- Current distribution network capacity varies across London, and there is likely to be capacity for sufficient growth in infrastructure in Central London. There may be more constraint in outer areas where drivers live, although slower chargers could be considered here.

- Throughout the project there has been continual growth in both Charge Point (CP) infrastructure and the average range of vehicles in the WS3 trial. Both of these factors will need to be factored in to modelling of future charging patterns.

Section 1 introduces this report and provides a brief overview of the project, the trials and the solutions that have been developed to support the Optimise Prime trials. **Section 2** details activities and findings from the return-to-home trials (WS1) carried out with Centrica's British Gas fleet. **Section 3** presents details of the interim findings from the WS2 depot trials in progress at Royal Mail depots in the London area. **Section 4** presents findings from the mixed trials (WS3), where data from Uber trips in Greater London is being analysed in order to achieve insights into the current and future impact of the PHV sector on charging and network infrastructure.

In all three trials the document revisits the experiments, gives an overview of the data that has been collected, presents interim conclusions and outlines next steps and changes planned based on experience from the first months of the trials. **Section 5** summarises the conclusions of the report, based on the work completed to date, and details the next steps in the trials that will be documented in deliverables D5 and D7. The appendices in **Section 6** present further details on the results of experiments conducted so far.

The development of the Optimise Prime solutions is now complete, although some further work to improve processes based on project learnings is likely to continue as the trials progress. The project partners had introduced sufficient EVs to their fleets to produce a statistically significant data set in advance of the start of the trials. Since then the EV fleet involved in the trials has continued to grow and there are in excess of 3,500 EVs involved in the trials.

The project is dedicated to creating solutions and data that will be applicable to all GB DNOs and this report provides the first evidence of the applicability of the methods being trialled in Optimise Prime. In addition, a significant amount of analysis has taken place both before and during the trial period in order to determine the potential impact of commercial EVs on distribution networks. These findings should prove valuable to any DNO considering how to plan for the future growth of commercial EVs. In addition, vehicle fleet operators planning to implement EV infrastructure and supporting IT systems can learn from the results presented herein and use the project's findings to optimise their EV transition. Although some aspects of the trial design are specific to Optimise Prime and its partners, the principles and objectives are applicable to all DNOs and to vehicle fleets planning a transition to ultra-low emission vehicles.

Table 3 shows the requirements of Deliverable D4, set out in the Project Direction, and where each item can be found within this report.

Table 3 – Deliverable D4 Requirements

Deliverable D4: Early learning report on the trials	
Evidence item	**Relevant section of the report**
Report setting out:	
how each trial is performing	Details can be found in sections 2.3, 3.3 and 4.3, relating to WS1, 2 and 3 respectively.
data gathered	Details can be found in sections 2.5, 3.5 and 4.5, relating to WS1, 2 and 3 respectively.

Deliverable D4: Early learning report on the trials	
insights gained	Details can be found in sections 2.7, 3.7 and 4.7, relating to WS1, 2 and 3 respectively.
changes required	Details can be found in sections 2.9, 3.9 and 4.9, relating to WS1, 2 and 3 respectively.

Optimise Prime is committed to sharing the project's outcomes as widely as possible. The project will continue to engage with a wide group of stakeholders throughout the fleet, PHV, technology and energy industries through a programme of events, reports, and the project website www.optimise-prime.com.

1 Background & purpose

This report, the fourth deliverable of the Network Innovation Competition (NIC) funded Optimise Prime project, details the early learnings from the three Optimise Prime trials. It demonstrates the work that has gone ahead in order to meet the trial objectives that were set out in Deliverable D1.

1.1 Introduction to Optimise Prime

Optimise Prime is an industry led EV innovation and demonstration project that brings together partners from leading technology, energy, transport and financing organisations, including Hitachi Vantara, UK Power Networks, Centrica, Royal Mail, Uber, Scottish & Southern Electricity Networks, Hitachi Europe and Hitachi Capital Vehicle Solutions. The role of each partner is described in Table 4.

Table 4 – Project Partners

Partner	Description	Project Role
HITACHI Inspire the Next	Hitachi is a leading global technology group committed to bringing about social innovation. Three Hitachi companies are project partners. Hitachi Vantara, Hitachi Europe, and Hitachi Capital Vehicle Solutions.	Hitachi leads the project, providing overall project management, energy and fleet expertise and project IT platforms. Hitachi is also developing tools for the depot trial.
UK Power Networks	Electricity DNO covering three licenced distribution networks in South East England, the East of England and London. The three networks cover an area of 30,000 square kilometres and over eight million customers.	London Power Networks (LPN) is the project's funding licensee. UK Power Networks provides networks expertise and is developing new connections methodologies and flexibility products.
Scottish & Southern Electricity Networks	The electricity DNO covering the north of the Central Belt of Scotland and Central Southern England.	Supporting experiments within the Central Southern England region, ensuring wider applicability of methods.
Royal Mail	Royal Mail provides postal delivery and courier services throughout the UK. It manages the largest vehicle fleet in the UK with over 48,000 vehicles based at 1,700 delivery offices.	Royal Mail is electrifying depots and operates EVs. Project tools will be tested in the depots and data from the vehicles will be captured.

Partner	Description	Project Role
Uber	Uber is the fastest growing PHV operator in the UK. Over 70,000 partner-drivers use the app in the UK, with the majority in and around London.	Uber is providing journey details from EV PHVs operating in London for the mixed trial.
centrica	Centrica is a UK based international energy and services company that supplies electricity, gas and related services to businesses and consumers.	The British Gas commercial vehicle fleet will participate in the trial. Centrica will also provide charging and aggregation solutions for the home trial.

Data from the use of over 3,500 EVs driven for commercial purposes is being gathered and analysed. The EVs are primarily based in London and the South East of England, although some in the home trial (WS1) are located throughout the UK. Optimise Prime is implementing a range of technical and commercial solutions with the aim of accelerating the transition to electric for commercial fleet operators while helping GB's distribution networks plan and prepare for the mass adoption of EVs. Through cross-industry collaboration and co-creation, the project is aiming to ensure security of energy supply while saving money for electricity customers, helping the UK meet its clean air and climate change objectives and transition to a net zero carbon economy.

Optimise Prime aims to be the first of its kind, paving the way to the development of cost-effective strategies to minimise the impact of commercial EVs on the distribution network. Commercial EVs are defined as vehicles used for business purposes, including the transport of passengers and goods. Compared to vehicles used for domestic purposes, commercial EVs will have a much greater impact on the electricity network because of their higher mileages and therefore higher electricity demand. The additional impact of commercial depot based EVs results from two factors: co-location of multiple EVs at a single depot location, and higher energy demand per vehicle resulting from higher daily mileages and payloads. The latter is also a factor when commercial EVs are charged at domestic locations.

Two DNO groups (UK Power Networks and Scottish & Southern Electricity Networks) across four licence areas are involved in the project. The consortium includes two of the largest UK commercial fleets (Royal Mail and British Gas) and a major PHV operator (Uber). This scale allows the industry to test different approaches to reducing the impact of vehicle electrification on distribution networks, in advance of mass adoption throughout the 2020s. This will also help understand the impact of a wide range of variables, including different network constraints, typical mileage, traffic characteristics, location (urban, sub-urban, rural) and availability of public "top-up" charging on the feasibility of electrification of commercial vehicle fleets.

By studying this diversity, the learnings generated by the project will be applicable to the whole of GB. Optimise Prime will deliver invaluable insights by using data-driven forecasting tools designed to allow networks to proactively plan upgrades. In addition, this project will create a detailed understanding of the amount of flexibility that commercial EVs can provide to the network through smart charging. Finally, a site planning tool has been developed to allow customers to model the impact of fleet electrification on their connection requirements. The tool will show customers how smart charging could be used to charge their vehicles within existing connection limits, and where this is not possible will provide the information necessary to request profiled connections (a new type of connection, providing a consumption connection capacity limit that varies throughout the day) from the DNO. Taken together, these form a set of innovative capabilities that allow for optimised utilisation of the network capacity, adopting a “flexibility first” approach and only reinforcing the network where no flexible alternative is suitable. This will result in cheaper costs for all customers, those connecting EV charge points, and all electricity bill payers.

Optimise Prime is seeking to answer three core questions, set in the project’s Full Submission Pro-Forma (FSP), relating to the electrification of commercial fleets and PHVs:

1. How do we quantify and minimise the network impact of commercial EVs?

We will gain a comprehensive and quantified understanding of the demand that commercial EVs will place on the network, and the variation between fleet and vehicle types. We will achieve this through large-scale field trials where we will capture and analyse significant volumes of vehicle telematics and network data. This data will enable the creation and validation of practical models that can be used to better exploit existing network capacity, optimise investment and enable the electrification of fleets as quickly and cheaply as possible.

2. What is the value proposition for smart solutions for EV fleets and PHV operators?

We will gain an understanding of the opportunities that exist to reduce the load on the network through the better use of data, planning tools and smart charging. Additionally, we will consider and trial the business models that are necessary to enable these opportunities. We will achieve this by developing technical and market solutions, and then using them in field trials to gather robust evidence and assess their effectiveness.

3. What infrastructure (network, charging and IT) is needed to enable the EV transition?

We will understand how best to optimise the utilisation of infrastructure to reduce the load on the network. This will be achieved through the collection, analysis and modelling of depot-based, return-to-home fleet and PHV journey data.

Answering these questions will enable network operators to quantify savings which can be achieved through reinforcement deferral and avoidance while facilitating the transition to low carbon transport. The trial will also assess the journey data to understand the charging and associated IT infrastructure requirements and implications for depot and fleet managers to be able to operate a commercial EV fleet successfully.

1.2 Purpose and structure of this report

The purpose of this report is to share the early learnings from the Optimise Prime trials. This includes all work done to date in analysing the data arising from the vehicles and infrastructure involved in the Home (WS1), Depot (WS2) and Mixed (WS3) use cases. This deliverable is an interim report, aimed at presenting initial findings from early analysis that may be of interest to project stakeholders. Throughout the remainder of the trials the project will compile a much richer dataset, allowing the results of all of the trial experiments to be reported in future deliverables.

1.3 Infrastructure, technology solution and trials context

The main elements of the infrastructure and technology solution are set out in the Full Submission Pro-forma (FSP) and are designed to support the three trials and two project methods (table 6 below). The trials align with the fleets of Optimise Prime's three project partners, each of which charge, representing home, depot and mixed charging as shown in Table 5.

Table 5 – Optimise Prime trials

Trial Number	Name	Partner	Description
1	Home Charging	British Gas Maintenance[1]	A field study of charging behaviour and flexibility with a return to home fleet.
2	Depot Charging	Royal Mail Delivery	A field study of charging behaviour and flexibility with a depot-based fleet. Additionally, the testing of profiled connections.
3	Mixed Charging	Uber PHV operator	A study based on analysis of journey data from electric PHVs.

Two methods will be tested through the trials. They are summarised in Table 6 below.

Table 6 – Optimise Prime methods

Method 1 **Smart demand response for commercial EVs on domestic connections**	Currently the additional peak demand would trigger reactive network reinforcement with the costs being entirely socialised as domestic and non-domestic use is blended together. In Optimise Prime we aim to separate the commercial loads to make them visible, testing demand response approaches with commercial EVs charging at domestic premises to identify and quantify the available charging flexibility.
Method 2 **Depot energy optimisation and planning tools for profiled connections**	Currently depots request a connection based on 'worst case' estimated peak demand, often triggering network reinforcement. The cost is part paid for by the connecting customer and part socialised across connected customers. In Optimise Prime we aim to design and test smart charging and energy optimisation 'behind the meter', at depots, to be able to conform to an agreed profiled connection. We are developing the tools and processes to calculate the optimal connection profile and infrastructure, for each site, to minimise the connection cost and/or capacity used. We will also test demand response approaches to identify and quantify the available charging flexibility from an optimal profile. The project will develop the commercial arrangements to enable the rollout of the method following the project.

[1] British Gas is a subsidiary of project partner Centrica.

1.3.1 Trials Overview

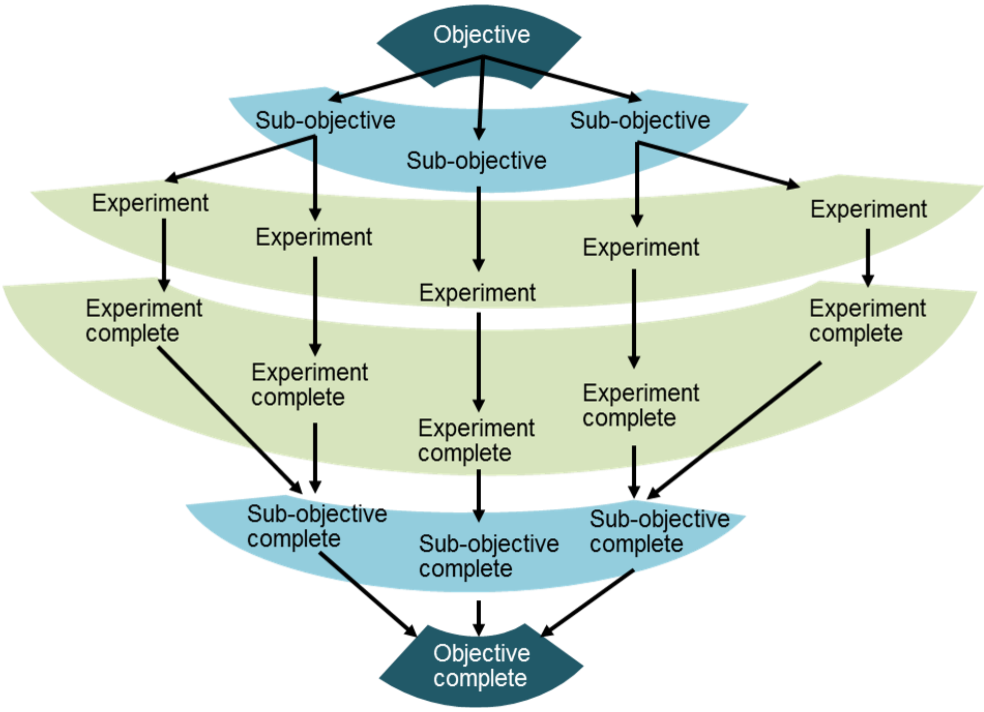
The Optimise Prime trials are being conducted using a common framework that was introduced in Deliverable D1 and further developed into a series of experiments in Deliverable D2. In brief, each of the trials is broken down into a series of objectives, listed in Table 7, based on the project's core questions, the table shows which of the objectives is relevant to each trial. The objectives are in turn broken down into sub-objectives, and experiments, as shown in Figure 1. The experiments can be carried out using data analysis, and completing the experiments will fulfil the objectives.

Table 7 – Objectives of the Optimise Prime trials

Objective	Home	Depot	Mixed
1. Create and validate models that predict the effects of electrification of commercial vehicles on the network to enable optimal investment	X	X	X
2. Assess the effects of profiled connections on fleet EV transition		X	
3. Assess smart electrification strategies	X	X	
4. Assess the ability of EV fleets to provide flexibility services to the DNO	X	X	X
5. Evaluate operational limitations to commercial fleet electrification	X	X	[2]

[2] Additional to the agreed FSP scope, but will be included if Uber are able to provide summaries of driver and/or passenger ratings in comparison with ICE vehicle data without additional cost to the project

Figure 1 – Trials objective deconstruction



The experiments have been designed to be iterative and were planned to all be run multiple times during the preliminary implementation phase (providing the necessary systems and data were in place), allowing for lessons to be learned from the first runs and applied to the execution approach before the formal trials began. Learnings from these preliminary activities are presented in this report, together with the initial results from the formal stage of the trials, where it has become possible to fully test aspects of the project methods such as profiled connections and flexibility services. As the trials progress and the project team's understanding of the data develops the experiments may be revised and the data analysis approach refined in order to fulfil the objectives more effectively and deliver additional insights.

Each execution is associated with the set of data engineering and data analysis features that are required to deliver it. For each trial, a specific set of data science models and analysis approaches is being developed according to the data science methodology, enabling insights and conclusions to be drawn from the data.

The iterations of experiments are designed to create a sample size sufficient to ensure statistical robustness in drawing conclusions from the analysis. This is being confirmed as the datasets are developed and trials carried out, with reference to the statistical approach that has been developed for the trials.

2 WS1 – Interim learnings from the Home Trials

2.1 Overview of the WS1 trials

WS1 is the home charging trial, focused on studying the charging behaviour and flexibility provision of a fleet where commercial EVs return to drivers' homes to charge. The trial is collecting data from the vehicles and chargers and testing the provision of flexibility services through the optimisation of vehicle charging by an aggregator, which will be analysed to model impact on the distribution network. In Optimise Prime, the trial involves Centrica's British Gas maintenance fleet of electric light commercial vehicles.

2.2 The WS1 Experiments

WS1 trials involve the execution of 14 experiments, listed in Table 8. Activities supporting the initial experiments have already been carried out, and are detailed throughout this section of the report, while others will follow later in the trial period, or will be reported in more detail in the next deliverable, D5, which focuses on initial learnings from business models and behavioural factors.

Some small changes have been made to the experiment hypotheses based on the project's growing understanding of EV operations and are noted in the table below.

Table 8 – WS1 Experiments

Experiment number	Hypothesis	Status
CEN_Ex_01	The relative contribution of unmanaged charging of charge-at-home EVs to overall home electricity consumption can be predicted using analysis of ICEV operation	Explored in this report
CEN_Ex_02	The relative contribution of 'smart' charging of charge-at-home EVs to overall home electricity consumption can be predicted using analysis of ICEV operation and unmanaged EV charging behaviour	Explored in this report
CEN_Ex_03	EV charging demand will be influenced by weather and seasonal events	Explored in this report
CEN_Ex_04	Charge-at-home EV charging causes low magnitude, local constraint on the LV distribution network but poses a more significant effect at higher voltages due to network clustering	To be explored in deliverable D7
CEN_Ex_05	Charge-at-home commercial vehicle electrification has higher DNO cost implications than depot-based vehicle electrification	To be explored in deliverable D7

Experiment number	Hypothesis	Status
CEN_Ex_06	**Originally:** Separate metering of commercial EV charging will save money for both the driver and the fleet operator[3] **Updated:** In the absence of an industry solution to the separation of commercial load on a domestic connection, software solutions based on data from CPs and telematics can provide an effective alternative, saving money for the driver and fleet operator	To be explored in deliverable D5
CEN_Ex_07	The Total Cost of Ownership (TCO) of charge-at-home EVs will be higher than ICEVs due to higher upfront costs	To be explored in deliverable D5
CEN_Ex_08	Distribution network constraints caused by charge-at-home commercial EVs will be minimised through combination of smart-charging and time of use (ToU) tariffs	Explored in this report
CEN_Ex_09	**Originally:** Charge-at-home vehicles with reactive operational behaviour with large distances/heavy loads are inappropriate for electrification[4] **Updated:** Reliance on home-based charging only is not suitable for vehicles with reactive operational behaviour, travelling large distances or carrying heavy loads	Explored in this report
CEN_Ex_10	The availability for charge-at-home EVs to be utilised for flexibility services can be predicted from 'smart' and unmanaged charging experiments	To be explored in deliverable D7
CEN_Ex_11	Flexibility from charge-at-home EVs will be best suited to long-term weekend contracts or short-term over-night contracts	To be explored in deliverable D7

[3] The change to CEN_Ex_06 clarifies that WS1 is using a solution to measure and reimburse EV charging costs rather than splitting metering, as the proposed Balancing and Settlement Code modification that would have allowed this (P379) has been withdrawn.
[4] CEN_Ex_09 has been reworded to clarify the meaning of this hypothesis.

Experiment number	Hypothesis	Status
CEN_Ex_12	**Originally:** Centrica drivers will prioritise operability over technological complexity of solution[5] **Updated:** 12a) Drivers' opinions of EVs and related smart technologies will become more positive with an increased exposure/experience. 12b) External factors rather than organisational factors are seen as main barriers to EV transition by corporate management. 12c) Smart charging needs to offer clear benefit to both the drivers and the fleet operator in order to be accepted.	To be explored in deliverable D5
CEN_Ex_13	Centrica as a fleet operator will prioritise TCO minimisation above operational aspects	To be explored in deliverable D5
CEN_Ex_14	Charge-at-home commercial EV fleets are not attractive to aggregators for flexibility provision	To be explored in deliverable D5

2.3 Status of the WS1 trials

WS1 have progressed significantly and trials began in full on 1 July 2021, once the minimum number of vehicles required to provide statistical significance, based on analysis by Imperial College Consultants (300), was on the road, and the systems were in place to record vehicle and charging activity. Since then, vehicle numbers have increased and there are now over 650 British Gas EVs on the road in the UK, with this number expected to increase to 1,000 as the trials progress. British Gas has adopted the Vauxhall e-Vivaro throughout their fleet, and these EVs are located throughout the UK, as shown in Figure 2.

The setting up of the WS1 trials presented more of a challenge to the project than the other trials, as its timeline was impacted by the slower than anticipated entry to the market of suitable EVs offering the required range and payload at an acceptable price. In turn this has had an effect on the development timeline of related project systems, as it was not seen as a good use of project resources to invest in development, and not possible to test solutions, before the EVs were confirmed.

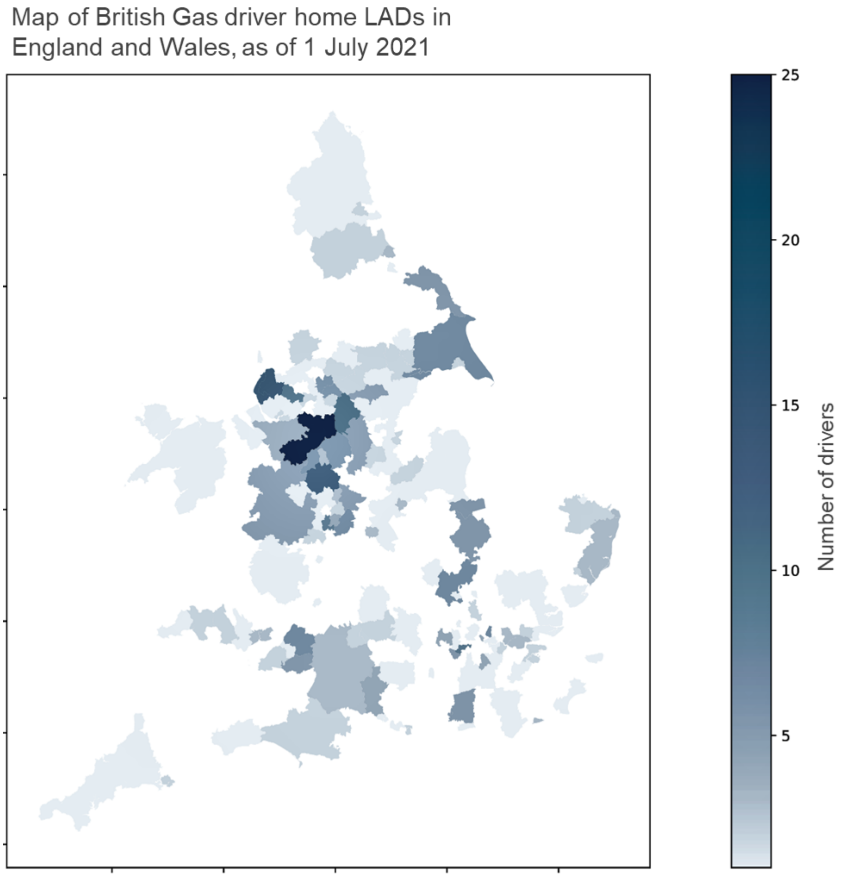
There are lessons to be learnt for other projects, and more generally for fleet managers, with regards to the uncertainties when planning the implementation of new technologies, and the need to allow sufficient flexibility to account for the increased likelihood of unexpected delays. While there are significantly more electric LCV models on the market now, compared to when the project began, supply remains a limiting factor on the ability of businesses to electrify their fleets. The complexity of rolling out EVs to a large fleet should also not be underestimated, as

[5] CEN_Ex_12 has been expanded into three hypotheses, reflecting the differing roles of the driver and fleet operator in transitioning fleets to EV.

it is necessary to coordinate the availability and fit-out of the vans with the availability of drivers and installation of CPs at homes. CPs were generally installed in advance of need, however in some instances drivers initially charged using public infrastructure where this was not possible.

Despite this, prior to the trials pre-trial executions of certain experiments were carried out which allowed the project team to create models and baselines through the analysis of British Gas' existing ICEV fleet, adding EVs to the analysis as they entered the fleet. Doing this allowed the project to refine plans for the trials and the outcomes of this initial analysis forms the core part of the learnings presented in this document.

Figure 2 – Location of British Gas EVs, by local authority in England and Wales



As more EVs join the trials there is an ongoing process of reconciliation between the telematics received from the vehicles and the charging events registered by the home charge points. In this type of analysis it is especially important to ensure that journeys and charging events are correctly linked in the analysis. Some inconsistencies were found in the two datasets that had to be resolved, so careful monitoring of the data sets proved necessary.

The flexibility functionality required for WS1 has also taken longer to develop than originally anticipated. This was partially a knock-on effect of the delay to vehicle deliveries, as it was difficult to fully design and test systems in advance of vehicles being available. These delays also caused some resource constraints within the project partners. The flexibility functionality is reliant on UK Power Networks' Active Network Management (ANM) system, which is being developed as a business-as-usual system outside of the scope of the project.

Interdependence on the development of new and complex systems such as this creates benefits in terms of showing the methods can work with Business as Usual (BAU) systems but does add risk to the project that needs to be appropriately managed. When it became apparent that the development timeline for the main ANM system would be extended the project switched to utilising a cloud-based version of the ANM system – this mitigated some of the delay, as did testing the integration of the different systems involved. While the project will collect a full year of telematics and charging data, the trialling of some flexibility products is being re-planned to ensure that all necessary experiments are carried out in the shorter period available.

The pre-trial and trial periods fell within a time when there may have been disruption to activities caused by the COVID-19 pandemic and the related restrictions in the UK. During the first lockdown in March-May 2020, British Gas engineers focused on mainly emergency callouts rather than routine maintenance, which may have impacted vehicle use, however subsequently schedules have returned to normal and there will have been little impact on the trial period.

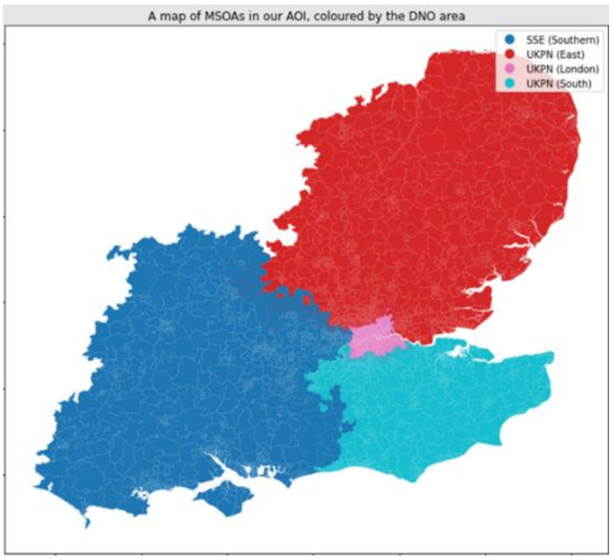
In addition to technical trials of the project methods and the analysis of data from vehicles the project has also carried out behavioural surveys with drivers of return to home vehicles. The interim results of the behavioural analysis will be reported in deliverable D5.

2.4 Methodology

The core data science analysis activities for this workstream principally utilises the EV telematics and CP data received as a monthly batch from Centrica. This covers all charging modes (unmanaged, smart and flexibility) anticipated in the Trials Design, and includes:

- Analysing the charging behaviour of a home-based fleet based on telematics and charging data
- Comparing the behaviour of EVs against ICEVs to model future network impacts
- Use of Local Authority Districts (LADs), and Middle Layer Super Output Area (MSOAs) to group vehicles, considering geographic factors such as regional variations in demand and clustering
- Analysis of the ability of home-based fleets to provide reliable flexibility services to the Distribution System Operator (DSO) in order to manage network constraints

Figure 3 – Map of the MSOAs in the AOI, coloured by DNO area



The initial Area of Interest (AOI) which will be the focus of the study covers the regions served by UK Power Networks' three DNO regions and SSEN's Southern region, shown in Figure 3. British Gas EVs throughout the rest of the UK will be included in future analysis where a larger data set is needed.

The approach for delivering the WS1 trials has been adapted since the trial design was originally agreed. While it was originally anticipated that the smart charging profiles and bids for flexibility would be developed on the project's main data platform, this work will instead be done by Centrica, utilising their expertise in, and systems developed for aggregation of distributed loads. This is not expected to have a material impact on learnings and should ensure that the flexibility responses generated in the project can be replicated with commercially available flexibility providers. As described above, Centrica will provide raw charging data to Hitachi for analysis and meter data from flexibility events to UK Power Networks to calculate performance and settlement.

2.5 Data being gathered to support the WS1 trials

The WS1 trials utilise a number of different datasets in order to analyse the charging behaviour of EVs. In these interim results, the focus has been on working with data from the existing ICEV fleet, as well as the initial analysis of EV data. The trials team has analysed historical ICEV data from August 2018 to February 2021 from around 7,000 ICEVs and is continuing to capture data from ~3,500 ICEVs in 160 LADs and more than 4,000 MSOAs. Events have been observed in 3,015 unique MSOAs across the AOI, this is shown in Figure 5 later in this chapter.

The data for the WS1 trials comes from two main sources – telematics (data captured from the vehicle) and meter data (captured from the CP used to charge the vehicle battery at the engineer's home).

2.5.1 Vehicle Telematics

Telematics from British Gas' EVs are compiled by the telematics provider and sent to Hitachi in a monthly batch for analysis. A similar historic dataset is collected for ICEVs to compare use of EVs with ICEVs and predict the impact of future growth. The specific data fields collected is described in Table 9.

Table 9 – Summary of telematics data fields

Data Collected for each trip
Device identifier
Trip start date, time, latitude, longitude, postcode
Trip end date, time, latitude, longitude, postcode
Trip distance in miles

2.5.2 CP meter data

There are two uses for CP meter data within Optimise Prime. It is used by Centrica to monitor their charge points to:

- Determine the amount of electricity the engineer should be reimbursed for charging their vehicle from their home for business purposes
- Enable smart charging schedules to be enacted (in this use case Centrica will delay charging to an off-peak time, but will not impose limits on charging rate), and to provide

evidence following flexibility events. Monthly batches of data are also shared with Hitachi for analysis.

There are two datasets of CP data:

- Per transaction dataset, a raw extract of events from Centrica's Charge Station Management System (CSMS), described in Table 10; and
- Flexibility settlement dataset, the data submitted by Centrica to the DNOs for the purpose of bids and settlements, described in Table 11.

Table 10 – Centrica CP metering data fields

Data Collected for each charge session
Charger and transaction ID
Start timestamp of transaction
End timestamp of transaction
Duration of charging event in minutes
Total kWh of charging event

Table 11 – Centrica flexibility CP data

Data Collected for each flexibility event
Flexibility UUID (Universally Unique Identifier)
Forward schedule (kW per half hour)
Planned deviation (kW per half hour)
Actual observed power, 15-minute average (kW)
Actual observed power, minute by minute (kW)

In addition to these main data sources, the WS1 trials are also able to make use of a number of common datasets used throughout the trials, such as geographical boundaries, which are used to group and display locations. Substation load and weather data are also available to the trial and will be used in future experiments in order to investigate impacts of home charging on the distribution network and the impact of weather on charging demand.

2.6 Analysis

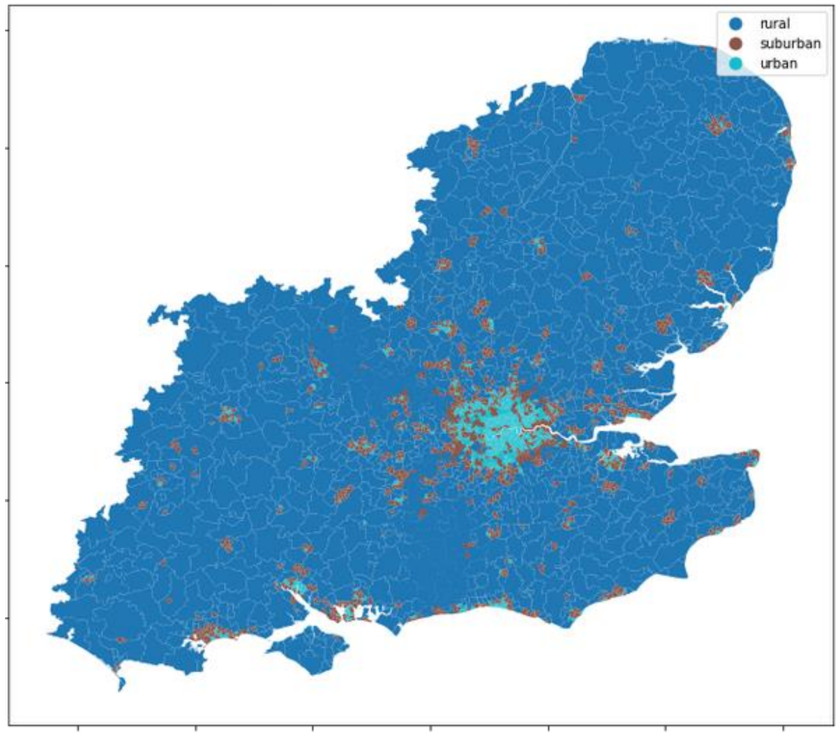
A number of executions of the experiments in the Home charging trial have been carried out with the datasets available to date. This primarily involved analysis of telematics data from the existing ICEV fleet, plus a smaller number of EVs. This section summarises the activities that have taken place so far as part of the analysis.

2.6.1 Formalising the AOI

The initial analysis focused on the core area of interest as shown in Figure 3. To extend the number of vehicles providing data into the trials, the AOI will be extended to GB as a whole for subsequent experiment runs. The AOI area is split down into smaller statistical areas, LADs and MSOAs, which are used for analysis of the location of vehicles and charging events.

This AOI was then divided into three groups, corresponding to "urban", "suburban" or "rural" areas, using an algorithm that allocated MSOAs to one of these groups according to their size. As each MSOA has a roughly constant population (between 5,000 and 15,000 with a mean population of 7,200 based on the 2011 census), the area of the MSOA indicates population density. Smaller MSOAs have dense populations and were therefore classified as "urban", while larger MSOAs have a more dispersed population. MSOAs were equally distributed across three quantiles of the area distribution, representing the three density types (urban, suburban, rural) (Figure 4). There are 1,005 MSOAs in each category.

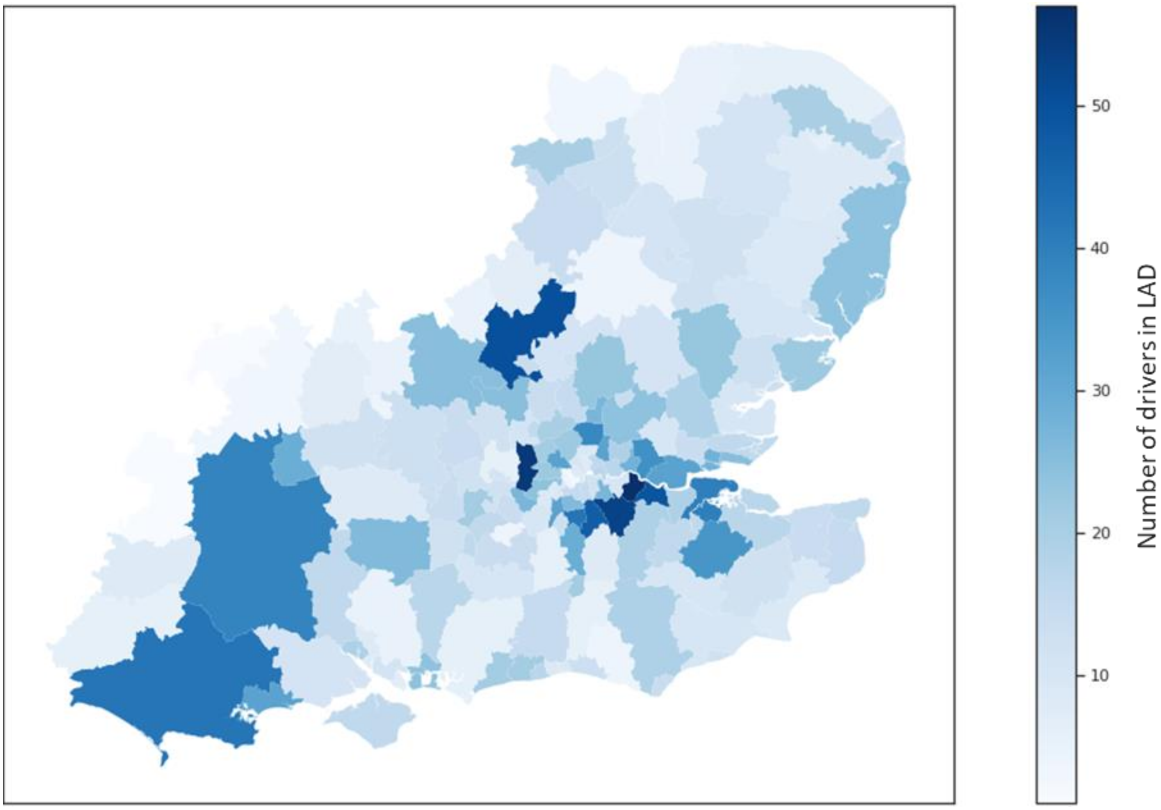
Figure 4 – Segmentation model for locations into the three location profiles: urban, suburban and rural



A Driver Home location model was developed to discern the dispersion of start/end events for the British Gas ICEV drivers, the same model can be applied to EVs. The model took the median of all the end locations for each driver over events where the haversine distance between the start and end location, essentially the distance “as the crow flies”, was less than one mile.

At the time of this initial analysis it was found that there were a total of 3,113 vehicles operating, with 3,002 of these being ICEVs and the remaining 111 EVs. The LADs with the most ICEVs were Dartford (195), Bromley (88) and Hillingdon (83), with nearby Hounslow containing the largest number of EVs (8). This distribution is shown in Figure 5.

Figure 5 – Plot of British Gas ICEV driver home locations (LAD), coloured by number of drivers.



2.6.2 Driver home location segmentation

Having observed the apportionment of drivers across the AOI, the trials used the same model to investigate the dispersion of drivers according to the characteristics of the MSOA they were assigned to: if it was “rural”, “suburban” or “urban”. As shown in Figure 6, it was found that both “rural” and “suburban” home locations for British Gas drivers were more common than “urban” MSOAs.

The trials then analysed these location segments according to the fuel type of the drivers’ vehicles (Figure 7). Rural locations were the dominant home for EV drivers accounting for 44% of the total, whereas for ICEV drivers there was a close split between suburban and rural. British Gas have confirmed that they allocated EVs based on interest shown by individual drivers, and did not target specific locations or routes, however the larger number of rural applicants may have been driven by the ease of installing charging infrastructure.

Figure 6 – Driver home location segmentations

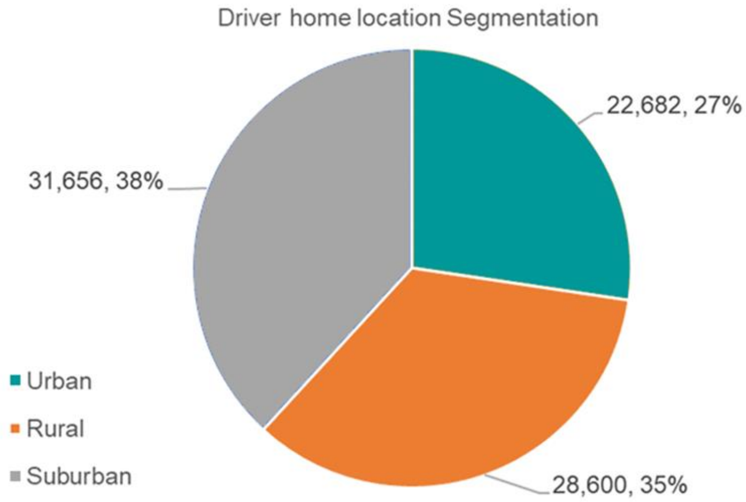
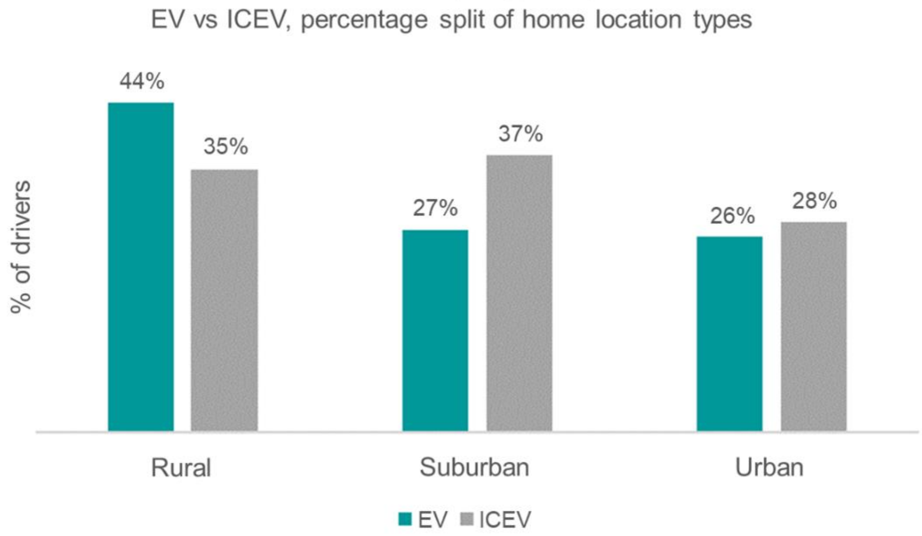


Figure 7 – Driver home location segmentations according to fuel type of vehicle. The Pie Chart on the left displays the results for EV drivers, and the right displays for ICEV drivers

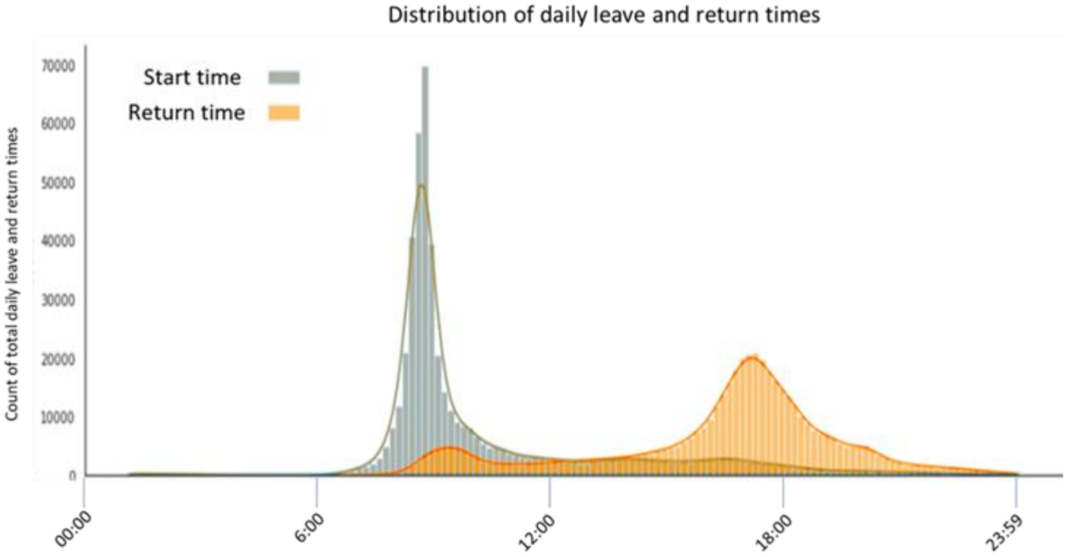


When the project analysed home location by number of charge events reported in the model, based on historical use of ICE vehicles, there were increases in charge events across all three home location types during the winter months of both 2019 and 2020. This is related to the seasonal nature of British Gas' work, such as servicing/repairing heating systems, where callouts are more common in cold weather. This could suggest that there was increased demand for electricity during this period which is important for consideration in further analysis on potential DNO impact and analysis of the charging load over the winter period of the trial.

2.6.3 Driver schedules

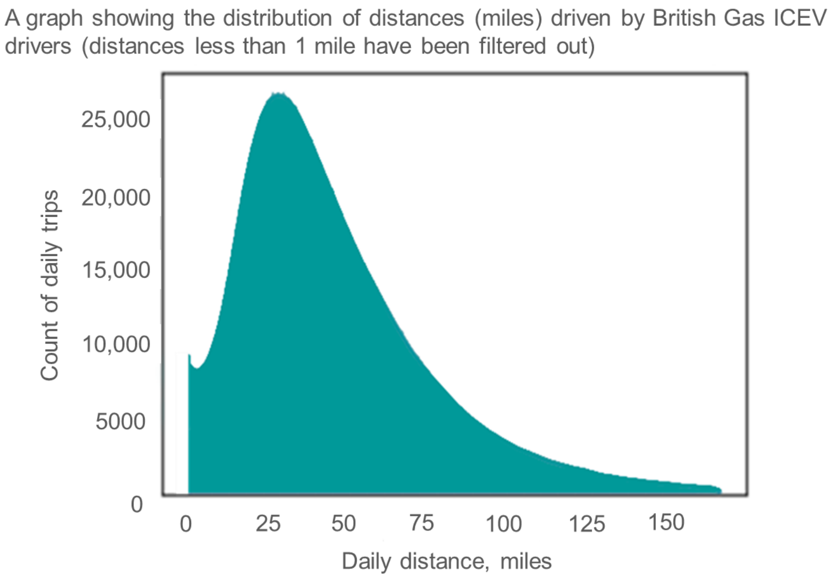
Early analysis, shown in Figure 8, indicated a general trend of British Gas drivers starting their shift at 9am and ending between 4:30-5pm. This appeared to be consistent across the different locational segments and there was little divergence when start and end times were analysed according to the DNO area in which the driver operated.

Figure 8 – Daily start and end times for ICEV schedules



The trials analysed the daily distances driven by each ICEV, as shown in Figure 9. The average distance that drivers were travelling was approximately 45 miles per day, with more distance covered by drivers during autumn and winter.

Figure 9 – Daily distances travelled by British Gas drivers, excluding any trips below one mile



2.6.4 Trip profiles

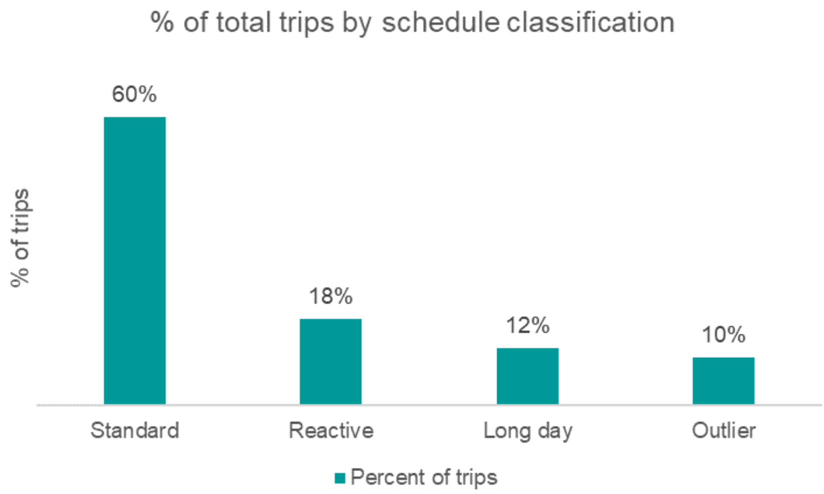
To gain a deeper understanding of British Gas' drivers' operations, four trip profiles were established and modelled against the previous findings on trip schedules and lengths. The profiles were:

- **Standard (Planned):** A trip profile would be denoted as Standard if the start time was between approximately 06:30 and 13:00 and end time was between approximately 13:00 to 20:00.
- **Reactive:** A trip profile would be Reactive if the schedule of activity did not constitute a Standard trip profile. Generally drivers with these profiles are 'on call' and can respond to customers at any time.
- **Long Day:** a trip profile would be a Long Day if the difference between the start time and the end time of a shift was at least 18 hours. This length of time was variable.
- **Outlier:** A trip profile would be an Outlier if the difference between the first start time and the last start time was less than 15 minutes, or the daily distance was less than one mile. The specific length of time and distance was variable.

The trials then applied these rules within the model to find the most common trip types that British Gas drivers were operating. Standard trip profiles made up the majority of operations at 60%, with Reactive profiles 18%, Long Day trips 12%, and Outlier trips the final 10% (Figure 10).

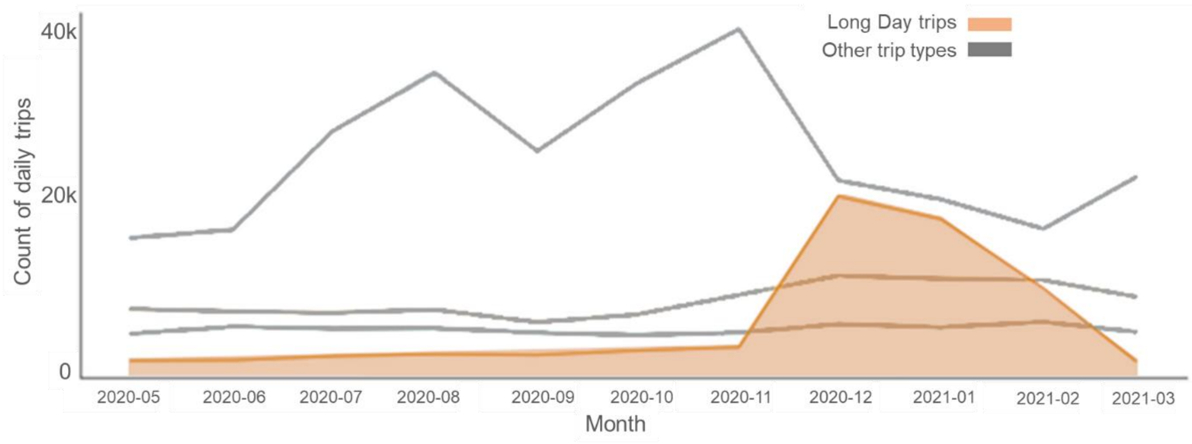
The outcome of this analysis was discussed with British Gas, who confirmed that it was generally in line with their operational patterns, and that they expect 'Reactive' and 'Long Day' routines, to increase in the winter when there is increased demand for repairs in addition to scheduled servicing. British Gas suggested that the longer days in Winter may not always result in longer mileages, as the increased demand often results in jobs being closer together, or the reactive nature of the work results in breaks between jobs.

Figure 10 – Driver Schedule profile segmentations



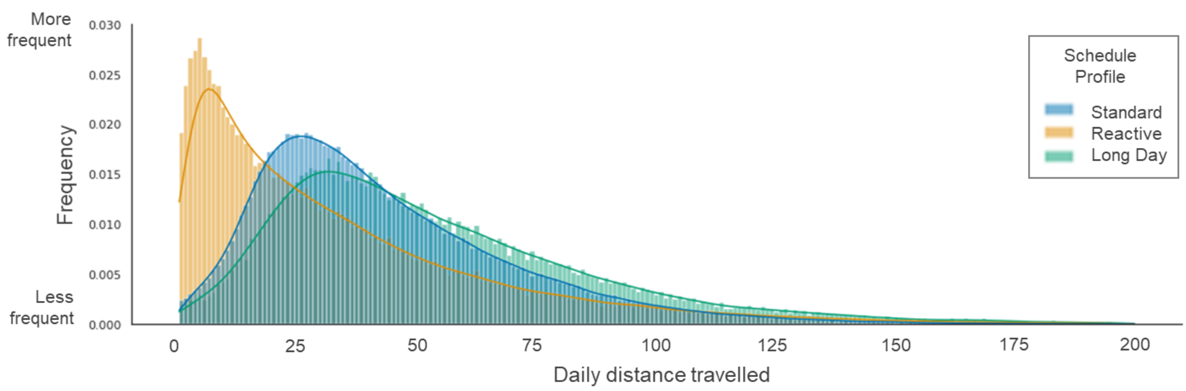
These trip profiles were then analysed against the time of year at which they occurred. Long Day and Reactive profiles were more common in the winter months, discussion with British Gas has confirmed that this is likely due to increased demand during in the colder temperatures for non-routine and emergency callouts (Figure 11).

Figure 11 – Volume of trip events plotted according to trip profiles, based on historic ICEV data



Reactive profiles were characterised by travelling far shorter distances, in contrast to Long Day profiles which saw a long tail of drivers travelling beyond 125 miles (though this would be in very small numbers). The median distance travelled per day for Standard profiles was found to be around 25 miles, well within the expected range of an EV (Figure 12).

Figure 12 – Observed distances travelled by ICEVs according to trip profile



With only EV telematics data from the summer of 2021 available at the time of writing, it is not yet possible to assert any definitive conclusions on the observed British Gas EV behaviour. Nevertheless, there have been some interesting aspects of the data that could represent early findings and the basis for further investigation. For instance, when comparing the EV schedule profiles with the ICEVs, it appeared that proportionally drivers that have volunteered for an EV could be more likely to be driving longer days. They also appeared to be proportionally less likely to operate reactive schedules, perhaps indicating lower confidences amongst engineers that EVs would reliably have sufficient range at the time of day or night when the trip was required, and therefore lower likelihood of engineers operating those shifts to volunteer for an EV.

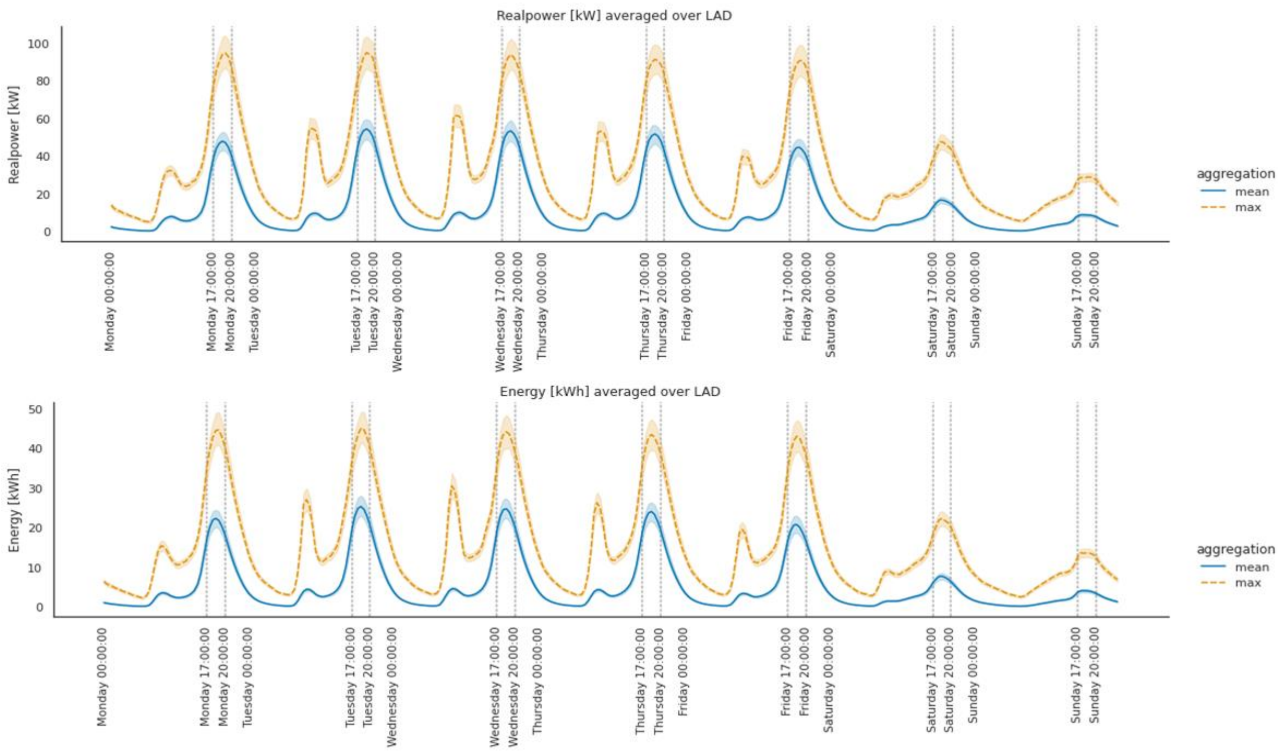
2.6.5 CP profiles

2.6.5.1 Unmanaged

Using daily departure and return times for the British Gas fleet from the telematics data, the expected power and energy demands on the grid resulting from the EV fleet were simulated. Due to the pattern of typical working hours for most drivers, peak energy demands from British Gas drivers would coincide with times of network constraint – the period between 5pm and 8pm – if the vehicles were to pursue unmanaged charging (Figure 13). Appendix 6.1 shows some examples of predicted demand on specific LADs.

In a worst-case scenario, with around 50 drivers operating in each LAD, shift schedules would suggest that around 30 simultaneous charge events could be initiated (equating to around a 60% of the chargers being in use simultaneously) the power demand from this scenario would be significant. The load on each domestic connection could become even higher if additional chargers were installed in the future to charge personal vehicles in addition to the van, or if higher power chargers were installed.

Figure 13 – Average Total Real power demand (kW) and Energy demand (kWh) derived from home-based, British Gas EV charging for a modelled LAD



2.6.5.2 Managed

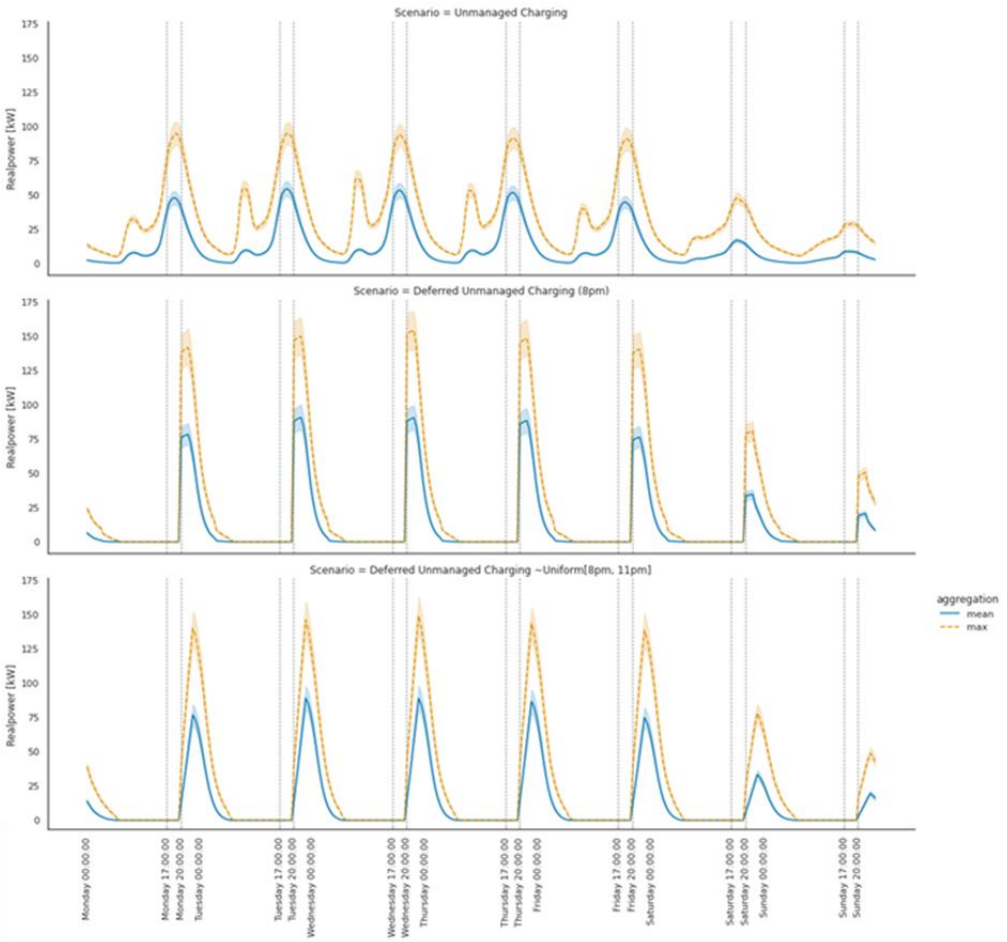
The Trials then investigated possible ways to mitigate this. Deferring the charging but not imposing a limitation on charging power wouldn't necessarily resolve the issue since it would only re-position the demand and create a new peak later in the evening.

This was found to be the case even when the start time for deferring charging was randomised across a three-hour period, as shown in Figure 14. Load Balancing, achieved by spreading the power requirements for charging EVs across the whole period while the vehicles are connected, would be more effective in reducing peak loads, creating a much lower but broader peak. Such a control method does however require an understanding of how long the vehicles will be plugged in to plan effectively and ensure all vehicles are charged by the time they are needed. It should be noted that this analysis has been completed using an estimation of load, and these results may differ when applied to the real-world charging demand currently being collected by the project.

Consequently, the trials determined at this stage that load balancing should be incentivised and not merely load shifting in order to minimise constraint. This will be explored further in the context of the flexibility trials as flexibility could potentially also be used to smooth out peaks resulting from deferred unmanaged charging.

UK Power Networks' Shift innovation project has recently considered a number of incentive mechanisms for managing the load from domestic charging, including time of use and capacity-based DUoS pricing, as well as flexibility services. The potential for these to apply to commercial vehicle charging in a domestic setting will be considered as the trial progresses. Through this work, similar conclusions were reached with regard to the impact of load shifting, which was found to reduce peak load when EV uptake was low, but create a potentially higher overnight peak at higher levels of adoption, especially when the underlying demand profile had existing overnight demand, such as overnight heating.

Figure 14 – Comparison of simulated power demand resulting from Unmanaged and deferred charging scenarios



2.7 *Insights gained*

While data analysis is at an early stage the project has already made good progress in progressing activities that will test the hypotheses posed by the trial experiments. Optimise Prime will be able to provide more conclusive results once a larger dataset is available. The following section draws on the analysis presented above and relates the findings to the experiments. Section 2.7.2 provides further insights gained outside the scope of the experiments that may be of interest to project stakeholders.

2.7.1 Addressing the experiment hypotheses

CEN_Ex_01 Initial hypothesis: The relative contribution of unmanaged charging of charge-at-home EVs to overall home electricity consumption can be predicted using analysis of ICEV operation

The trial's analysis, based on the study of ICEV data, has found that the charging of EVs is likely to significantly increase electricity consumption at drivers' homes.

Based on this analysis it can be seen that unmanaged charging is likely to result in a peak in charging demand between 17:00 and 20:00, coinciding with peaks in household demand on the grid.

The accuracy of this modelling will be confirmed as the project collects real-world EV data from the fleet.

CEN_Ex_02 Initial hypothesis: The relative contribution of 'smart' charging of charge-at-home EVs to overall home electricity consumption can be predicted using analysis of ICEV operation and unmanaged EV charging behaviour

Both unmanaged and smart charging behaviour has been predicted based on the EV data. For smart charging two different models were created – deferred charging, where only the time of charging was altered and load balancing, where the peak load on the network is minimised.

As with CEN_Ex_01, further work to verify these results against actual EVs will continue as more data is captured and smart charging is tested.

CEN_Ex_03 Initial hypothesis: EV charging demand will be influenced by weather and seasonal events

The seasonal demand pattern has been studied based on British Gas' ICEV data. It has shown that for this fleet there is predicted to be significant variation in seasonal demand as a result of an increased numbers of trips and greater mileage in winter months.

Once the project has an EV charging dataset covering the full year the project will be able to further this analysis and separate the impact of changing shift patterns (which may be specific to certain fleet types) from seasonal effects on EV efficiency.

CEN_Ex_08 Initial hypothesis: Distribution network constraints caused by charge-at-home commercial EVs will be minimised through combination of smart-charging and time of use (ToU) tariffs

Smart charging behaviour has been predicted based on the ICEV data. The modelling shows that smart charging could have a significant impact on power demand, however the type of smart charging implemented needs to be chosen carefully. Simply shifting the demand later may result in higher peak demand if charging events that were more spread out during the day/evening were shifted to start simultaneously. Smart charging that is based on load spreading or balancing over the time the vehicle is plugged in could reduce peaks in EV demand significantly.

Further work to verify these results against trials of unmanaged and smart charging will continue as more data is captured. The project will also utilise the data captured from British Gas charging events in modelling the impact of home-based commercial vehicles on distribution network constraints.

CEN_Ex_09 Initial hypothesis: Reliance on home-based charging only is not suitable for vehicles with reactive operational behaviour, travelling large distances or carrying heavy loads

To date, the study of the usage of the British Gas ICEV fleet has identified that the majority of journeys that are currently performed by British Gas drivers should be possible with the EV that has been chosen for British Gas using at-home charging.

Drivers undertaking ‘reactive’ work, outside of normal hours or schedules have been found to generally drive shorter than average distances, so this mode of work is unlikely to be a barrier to electrification. However, at this stage in the rollout relatively few ‘reactive’ schedules are being operated by EVs – this may be due to driver perceptions affecting the decision to convert to EV or the seasonality of reactive work.

There are some longer trips taken, in the range of 140-200 miles that might require top-up charging in order to be carried out by current generation EV vans. However these trips are very few in number. British Gas provide drivers with access to public EV charging networks for this purpose. Longer trips carried out by the British Gas fleet are generally focussed around the winter months, so it is possible that these may coincide with other seasonal effects that reduce the efficiency of EVs.

Further analysis on this will follow, to ensure that real world performance throughout the year matches the theoretical capabilities of the vehicles.

2.7.2 Other learnings

In addition to the learnings that directly address the trial hypotheses Optimise Prime has generated the following learning from trialling return-to-home charging in WS1:

- **The complexity of rolling out large fleets of vehicles**: throughout the project, the availability of sufficient vehicles has been a key constraint. Even after orders are confirmed, the process of getting the vehicles on the road, and ready to participate in the trials is complex and time consuming. The fleet operator needs to balance the timing of vehicle availability and fit out with ensuring CPs are installed in the right places and that a driver is ready to swap vehicles at the required time. On top of this, when engaging in monitoring or smart charging of vehicles, it is necessary to ensure that there are processes in place to accurately map the vehicles with the CPs and record any changes.

2.8 Next steps

The next stage of the WS1 trial will focus on extending the initial analysis and insights developed primarily from ICEV telematics data, using EV telematics and CP datasets, as more data becomes available. This will enable comparison of predicted charging behaviour with observed charging behaviour, under both unmanaged and smart charging conditions, to give a more accurate picture of the differences between idealised and actual EV operations, and validate the impact in terms of timing and magnitude of power demand on the electricity distribution network.

The trials are also gathering and analysing a large dataset of flexibility events: British Gas EVs will have the opportunity to participate in more than 240 flexibility events over the remainder of the formal trial period. This will provide valuable insight into the potential for return to home EV fleets to deliver reliable and cost-effective flexibility services.

2.9 Changes made or planned to the trial methodology

No significant changes are planned to be made to the WS1 trials at this time. Some minor changes have taken place in order to respond to practical constraints on trial delivery:

- Due to knock on delays in the development of the flexibility systems, the flexibility service trials have been re-cast over a shorter period within the trials. It is not expected that the learning outcomes will be impacted by this change.
- Hitachi and Centrica revised some aspects of how flexibility and smart charging are controlled and analysed within the project, with Centrica controlling smart charging interventions directly. This change should better mirror how an aggregator would manage their EV fleet while still delivering value to the project. As part of this, Centrica’s flexibility service provider platform will connect directly to the UK Power Networks ANM for bidding and dispatch of flexibility events.
- While Optimise Prime was initially focused only on vehicles in the UK Power Networks and SSEN DNO areas, it is now intended to make use of British Gas EVs throughout GB in the project experiments where it is not necessary to align charging events to geographic locations. This will allow a larger, more statistically robust number of EVs to participate in the trials, and allow larger flexibility responses.
- When the trial experiments were originally written it was thought that the trial would have access to actual home energy usage for the trial locations. This is not available as it is controlled by each householder. Standard profiles will be used where it is necessary to consider the impact of EV charging and flexibility on whole house load.
- As British Gas’ EV fleet plans have developed it has become necessary for some vehicles to be charged with public, rather than home, charging. In some cases this is temporary, while awaiting CP installation, while in a small number of cases it is permanent where home charging could not be implemented (e.g. due to lack of off-street parking). The telematics from these vehicles will be utilised by the trials, but they cannot take part in flexibility trials or analysis of charging load.
- As noted in Table 8, some minor changes have been made to the wording of the experiment hypotheses.

3 WS2 – Learnings from the Depot Trials

3.1 Overview of the WS2 trials

WS2 is the depot charging trial, focused on managing the charging of commercial EVs that return to a depot each day at the end of their shifts. The trial is collecting data from the vehicles and chargers and is testing the provision of flexibility services through the control of vehicle charging and the ability of depots to maintain a profiled connection. In Optimise Prime, the trial involves over 300 electric light commercial vehicles at nine Royal Mail depots as shown in Table 12. The varying sizes of depots, socket numbers and EV fleets are expected to provide the trials with insights regarding the applicability of the methods to different depot types.

Table 12 – WS2 Depots, CPs and EVs (the exact number of EVs at each site can vary due to Royal Mail's operational requirements)

Depot	Charge Sockets	EVs
Bexleyheath	6	12
Camden	6	12
Dartford	22	26
Islington	24	24
Mount Pleasant	87	125
Orpington	6	12
Premier Park	51	49
Victoria	6	12
Whitechapel	33	32
Total	**241**	**304**

3.2 The WS2 experiments

The WS2 trials are the only ones to address all five trial objectives, and as a result there are 20 experiments associated with this workstream as shown in Table 13. Some minor changes have been made to the wording of the hypotheses for RM_Ex_14 and RM_Ex_20 as explained in the table below.

Table 13 – WS2 Experiments

Experiment number	Hypothesis	Status
RM_Ex_01	The impact of unmanaged EV charging on Royal Mail depot electricity demand can be predicted using analysis of ICEV operation	Detailed in this report
RM_Ex_02	The impact of 'smart' EV charging on Royal Mail depot electricity demand can be predicted using analysis of ICEV operation and unmanaged EV charging behaviour	Detailed in this report
RM_Ex_03	EV charging demand will be influenced by external factors such as weather and seasonal events	To be explored in deliverable D7

Experiment number	Hypothesis	Status
RM_Ex_04	The load profile of Royal Mail depots can be predicted based on the degree of electrification of the fleet and charging mode adopted (unmanaged or 'smart')	Detailed in this report
RM_Ex_05	The impact of installation of other LCTs on load profiles of electrified depots can be predicted	To be explored in deliverable D7
RM_Ex_06	The need for network reinforcement resulting from depot fleet electrification can be mitigated through profiled connections	Detailed in this report
RM_Ex_07	LV distribution network impacts resulting from depot EV charging can be predicted	To be explored in deliverable D7
RM_Ex_08	HV distribution network impacts resulting from depot EV charging can be predicted	To be explored in deliverable D7
RM_Ex_09	Depot vehicle electrification has lower DNO cost implications than return-to-home vehicle electrification	To be explored in deliverable D7
RM_Ex_10	EV load shifting can enable adherence to a profiled connection without exposing the DNO to unacceptable risks	To be explored in deliverable D7
RM_Ex_11	Profiled connection agreements are financially advantageous to both depot operator and DNO	To be explored in deliverable D5
RM_Ex_12	Profiled connection agreements and flexibility services reduce fleet TCO	To be explored in deliverable D5
RM_Ex_13	Profiled connection agreements reduce lead time and costs to electrify fleets	To be explored in deliverable D5
RM_Ex_14	Smart electrification strategies *(load balancing, flexibility and profiled connections)*[6] reduce DNO costs	To be explored in deliverable D7
RM_Ex_15	Optimisation of depot LCTs with the EV fleet creates additional benefits	To be explored in deliverable D7
RM_Ex_16	The availability for depot based EVs to be utilised for flexibility services can be predicted from 'smart' and unmanaged charging experiments	Detailed in this report
RM_Ex_17	Standard connection agreements allow for higher availability of cheaper flexibility compared to profiled connection agreements	To be explored in deliverable D7
RM_Ex_18	Flexibility will only be a viable option to depots if procured on long-term contracts for weekend or over-night periods	To be explored in deliverable D7
RM_Ex_19	DNO current flexibility requirements are unlikely to be met by depot based EVs	To be explored in deliverable D7

[6] The italicised text has been added to clarify the meaning of 'smart electrification strategies' in RM_Ex_14

Experiment number	Hypothesis	Status
RM_Ex_20	**Originally:** Royal Mail depot staff will favour operability over technological sophistication of the solution[7] **Updated:** a) *Drivers' opinions of EVs and related technologies will become more positive with an increased exposure/experience.* b) *Depot managers are largely supportive of the switch to EVs, despite some operational challenges.* c) *External factors rather than organisational factors are seen as main barriers to EV transition by corporate management.* d) *Corporate managers are largely in favour of smart charging, while depot managers (operational level) are sceptical.*	To be covered in deliverable D5

3.3 Status of the WS2 trials

The WS2 trials began in full on 1 July 2021. At this point the minimum number of vehicles required for the trials was on the road, and the systems were in place to record vehicle and charging activity.

Prior to the trials several pre-trial executions of experiments were carried out which allowed the project to create a number of models and baselines through the analysis of Royal Mail's existing ICEV fleet and the initial group of EVs.

Since the beginning of the trial period the project has continued to capture data from EVs and infrastructure. In addition, several initial trials of the project methods have taken place, including running profiled connections and flexibility events. These initial trials have largely been run to prove the functionality of these methods and throughout the trial period several further tests will be run with differing requirements in order to gauge the ability of the Royal Mail sites to provide useful services to the distribution networks. The initial results of this activity is presented in this report.

The COVID-19 pandemic has occurred during the Optimise Prime project. This is likely to have had some impact on the usage of Royal Mail vehicles in the period of the trials and the period immediately before. For example, some working practices at Royal Mail, such as double crewed vehicles, were suspended to allow for social distancing.

3.4 Methodology

The WS2 trials involve several activities aimed at simulating EV demand for EV depots, testing these simulations against real-world data gained at Royal Mail sites together with the testing of different types of flexibility including profiled connections, forward option and day ahead auction.

[7] RM_Ex_20 has been expanded into four hypotheses, reflecting the differing roles of the driver, depot manager and corporate fleet manager in transitioning fleets to EV.

Modelling tools have been developed and applied to simulate a week of depot operations with a certain number of EV and CP assets under different charging modes (unmanaged charging, and different smart charging regimes).

The aim was to estimate impact of fleet electrification on network load, relating to potential infrastructure upgrades required in the future. The primary type of smart charging modelled is referred to as 'peak load minimisation', a charging mode aiming to minimise this network impact. Secondly, a cost minimisation version of smart charging was also modelled, aiming to explore the value of smart charging to the fleet operator through the minimisation of the cost of electricity. This modelling was completed for simulation purposes, based on inputs regarding the fleet's existing ICEV operations and proposed EVs. The early modelling work also contributed to the development of the logic for a self-service site planning tool that allows fleets to model the connection requirements of their planned fleet electrification.

Physical CPs, together with a control system that can alter charging to requested setpoints have been installed at Royal Mail depots, as described in the previous deliverables D2 and D3.

Throughout the trial period the Royal Mail depots are trialling a programme of charging management functionalities, including unmanaged charging (as a base case), smart charging methodologies, profiled connections and provision of flexibility services on request from the DNO. These real-life trials are allowing the project to verify the accuracy of the predictive models.

3.5 *Data gathered to support the WS2 trials*

The WS2 trials utilise a number of different datasets in order to both analyse the impact of depot charging and to optimise the charging of vehicles within the depots.

Data from charge points is key to understanding when vehicles are charging and how much power is being used. This data is received in real-time in the Hitachi solution from Nortech iHost, which in turn collects the data from the CPCs and CPs at each site. The main data fields collected are described in Table 14.

Table 14 – WS2 CP Data collected via iHost

Dataset	Data Collected
iHost Measurements	EVSE and Socket Identifiers
	Data Point type (describes the state of the CP – e.g. Available, Preparing, Charging, Faulted; or a power value – total energy (kWh), real power (kW), current limit (A).
	Measurement timestamp
	Measurement value
	Tag ID (the RFID tag that is authenticated with the socket)
iHost Charging Events	Record, EVSE and Socket Identifiers
	Tag ID (the RFID tag that is authenticated with the socket)
	Charging Start timestamp
	Charging End timestamp

In order to derive the total load at each site, data is collected from Panoramic Power devices that monitor incoming feeders. This data is retrieved every five minutes and is captured at a one-minute granularity. Table 15 shows the data recorded by Panoramic Power.

Table 15 – WS2 site load data collected via Panoramic Power

Panoramic Power Dataset
Device and Site Names/IDs (most sites have multiple devices connected across multiple phases and/or feeders)
Measurement time in UTC and resolution of measurement in minutes
Measurement of power in W
Measurement of energy in Wh
Current (A), Voltage (V) and power factor figures are captured but are based on calculation and not actual measurement.

There are three telematics systems in place for different types of vehicles which have varying measures and data frequencies.

Axodel is the main source of data from Peugeot vehicles. Data is received in near real time via an API (Application Programming Interface) for use in optimisation and is saved for analysis once per day. Table 16 shows the main fields collected.

Table 16 – WS2 Telematics data collected via Axodel

Axodel telematics dataset
Vehicle Metadata (Vehicle Identification Number (VIN), Brand, Model, age, fuel type, etc.)
Date of measure
Meter counter (total distance travelled by the vehicle) and Trip Distance (hm)
Position of vehicle (latitude and longitude)
Fields showing whether the vehicle is plugged in, charging (and at what power)
Battery state of charge

Mercedes telematics provides a similar set of data for Mercedes vehicles. Some older Peugeot vehicles are connected to a Trimble telematics system. Trimble only provides the project with data in periodic batches, and so can be used for analysis, but not as part of real-time optimisation. The project also makes use of a Trimble telematics dataset that covers Royal Mail ICEV from 2018 to present. This data is similar to the other telematics datasets, but does not include items specific to EVs.

Historical Meter data for the Royal Mail depots involved in the project is also used – this takes the form of half-hourly meter data per MPAN in kWh.

3.6 Analysis

A number of executions of the experiments in the depot charging trial have been carried out with the datasets available to date. This primarily involved analysis of telematics data from the existing ICEV and EV fleets. This section summarises the activities and insights gained from this initial analysis.

3.6.1 Operational schedules

The Trials analysed the ICEV operational schedules at a depot level using a clustering algorithm based on the telematics data. For each depot, data on vehicle movements were organised to categorise operational groups (according to the depot leave time, depot return time and average daily mileage), while each were ascribed the proportion of the total fleet they represented at their depot.

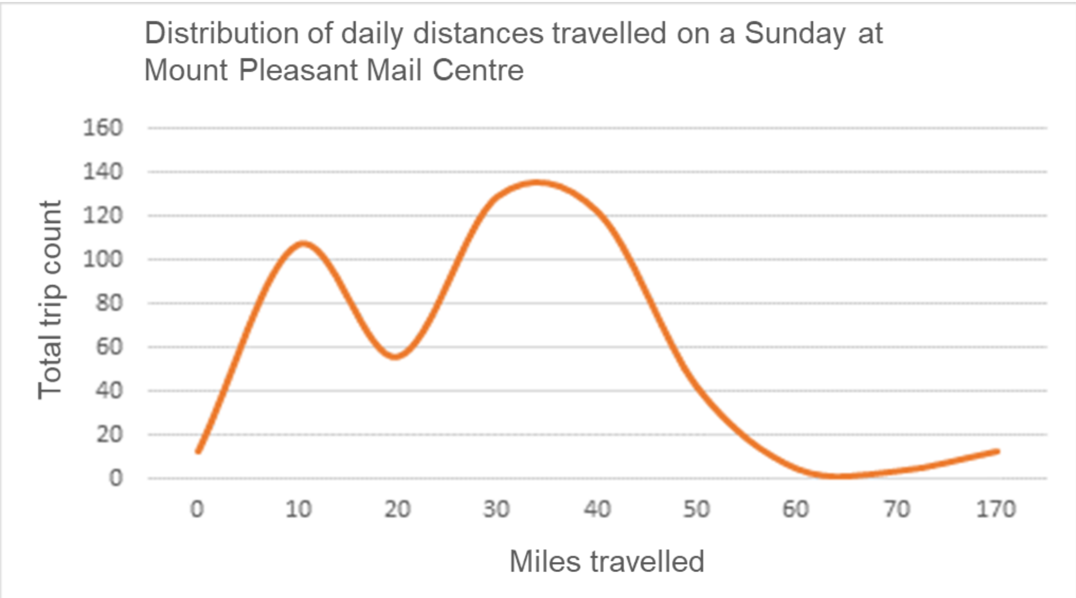
Generally, there were three main schedules that accounted for the majority of operations at each depot (see example schedules for Whitechapel, Table 17) supplemented by 1-4 minor schedules that made up the balance of journeys.

Table 17 – Whitechapel's operational schedules

Schedule	Depot Leave Time	Depot Return Time	Daily Distance (miles)	% of Vehicles
1	07:00	18:30	25.1	36
2	08:30	13:00	11.3	33
3	10:00	18:00	21.6	27

Activity on Sunday was rare across the Royal Mail depots, although the data suggested there were occasional trips occurring at Mount Pleasant and Dartford. These trips were inspected and at Mount Pleasant it was found that the trips had an average distance of 35 miles (vs. a weekday average of around 20 miles). This suggested they could be relevant, non-trivial business activity (Figure 15) and it was confirmed with the depot manager at Mount Pleasant that the depot was undertaking operations on Sundays.

Figure 15 – Distances travelled by vehicles at Mount Pleasant depot on Sundays



Through detailed analysis of the ICEV telematics, the trials were able to construct a reliable picture of the business operations of the fleet at each of these depots. Understanding this is fundamental to being able to model and plan electrification at these sites, and ultimately supporting the transition of the ICEV fleet to EV. Having built a solid understanding of these operational schedules, the trials progressed to modelling EVs fulfilling those operations at the Royal Mail depots.

3.6.2 Trip profiles, per depot

3.6.2.1 Expected EV behaviour and impact

Initial analysis on EV operational schedules revealed some interesting deviations in how EVs are operated compared to ICEVs. ICEVs were generally found to operate three main schedules, as shown for the example of Dartford (Table 18), with other minor schedules also in operation for a smaller proportion of the fleet.

Table 18 – Operational schedules for ICEVs at Dartford

Schedule	Depot Leave Time	Depot Return Time	Daily Distance (miles)	% of Vehicles
1	08:30	13:30	14.2	34
2	05:30	13:30	19.8	32
3	09:00	18:00	41.4	20
4	06:00	17:30	36	13

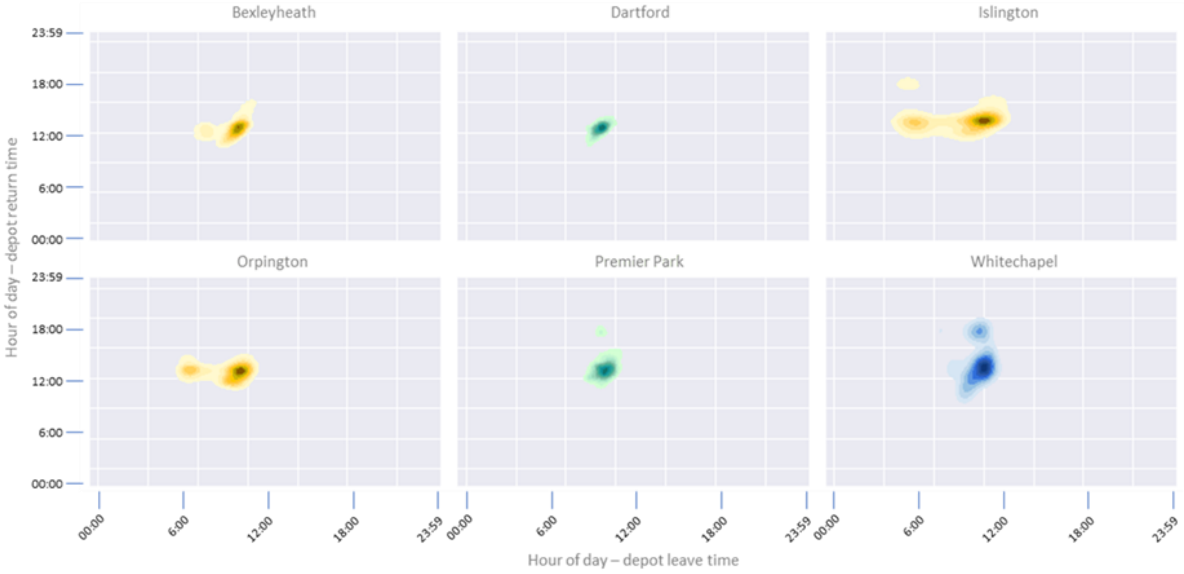
By contrast, Royal Mail was found to operate their Peugeot EVs at Dartford on more stable schedules, with all following the same pattern of leaving at 8:30am and returning at 13:30pm, travelling an average of 18.9 miles (Table 19). This EV behaviour was mirrored at Premier Park, with both sites depicted on the density plot (Figure 16) as one concise plot connecting concentrated leave and return times. Royal Mail depots have considerable flexibility over how vehicles are allocated to routes, so it is likely that EVs have purposefully been allocated to a specific route where depots have a variety of EVs and ICEVs. It should also be noted that the EV data covers a shorter period and may not take account of seasonal changes of schedule.

Table 19 – Operational schedules for EVs at Dartford

Schedule	Depot Leave Time	Depot Return Time	Daily Distance (miles)	% of Vehicles
1	08:30	13:30	18.9	100

At Bexleyheath, Orpington, Islington and Whitechapel, EVs also followed a second operational schedule, resulting in a fainter cluster accompanying a prominent cluster, illustrating some vehicles were leaving and returning at alternate times. It should be noted that EVs have been monitored for a more limited time, so further schedules may become apparent with seasonal variation.

Figure 16 – Density plot of depot departure and return times for Royal Mail EVs, colour represents schedule type



3.6.3 Charging load modelling

3.6.3.1 Unmanaged Charging

The trials modelled unmanaged charging schedules for each depot constructed from the operational schedules of ICEVs. The energy requirements for the fleet were calculated using information on EV battery capacity and vehicle ranges, according to manufacturer's published data, coupled with the daily distances and schedules of the vehicles. These energy requirements represented the battery usage of EVs in kWh needed for the vehicle to fulfil its daily operations. Using this information, it was possible to simulate the variation in total fleet energy requirements (kWh) and charging load (kVA) throughout a seven day period for each depot.

3.6.3.2 Smart, managed charging

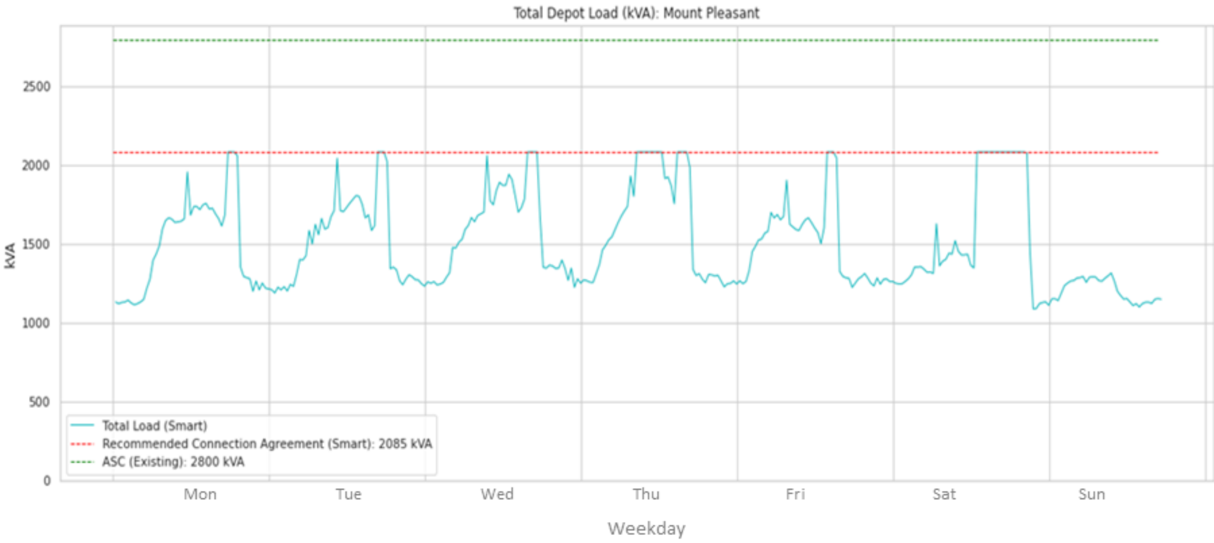
Having simulated the viability of using unmanaged charging to deliver the charging requirements of the fleet, the trials worked to develop further simulation models to evaluate how smart charging could achieve benefits for Royal Mail and for the grid. The model enabled prediction of energy requirements, plug-in/plug-out time and state of charge (SoC) for vehicles at each depot, while incorporating times vehicles are able to charge at according to operational schedules learnt from telematics data.

This facilitated the generation of smart charging schedules that could either minimise the peak load required to charge an EV fleet at each depot, or minimise the energy cost of charging the vehicles. These two simulations of smart charging behaviour were named **peak load minimisation** and **cost minimisation**. The logic underpinning this smart charge modelling by the Optimise Prime team of Data Scientists is in Appendix 6.2.

The trials applied these models to develop smart charging simulations of eight Royal Mail sites: Bexleyheath, Camden, Dartford, Islington, Mount Pleasant, Orpington, Premier Park and Whitechapel (see example for Mount Pleasant in Figure 17) The ninth depot at Victoria had not been added to the project scope when this analysis was carried out. The results indicated that using smart charging could yield benefits for both Royal Mail and the DNO. Generally, these benefits were as follows:

1. Using the model enabled a lower value of maximum demand being possible within the connection agreement, when compared to a business-as-usual unmanaged case, as the peak power demand could be reduced while still providing sufficient charge to the fleet.
    a. This would minimise cost for Royal Mail as there would be no need to upgrade their current Authorised Supply Capacity (ASC), saving capital, resource and time
    b. This would benefit the DNO as network capacity could potentially be utilised by other customers.
2. Using the smart schedule directly facilitated electrification of more vehicles within the current ASC.
    a. This would benefit Royal Mail as it would remove a potential barrier to the further electrification of their fleet.

Figure 17 – Total charging load mapped over a seven day period according to a peak load minimisation managed smart charging schedule at Mount Pleasant

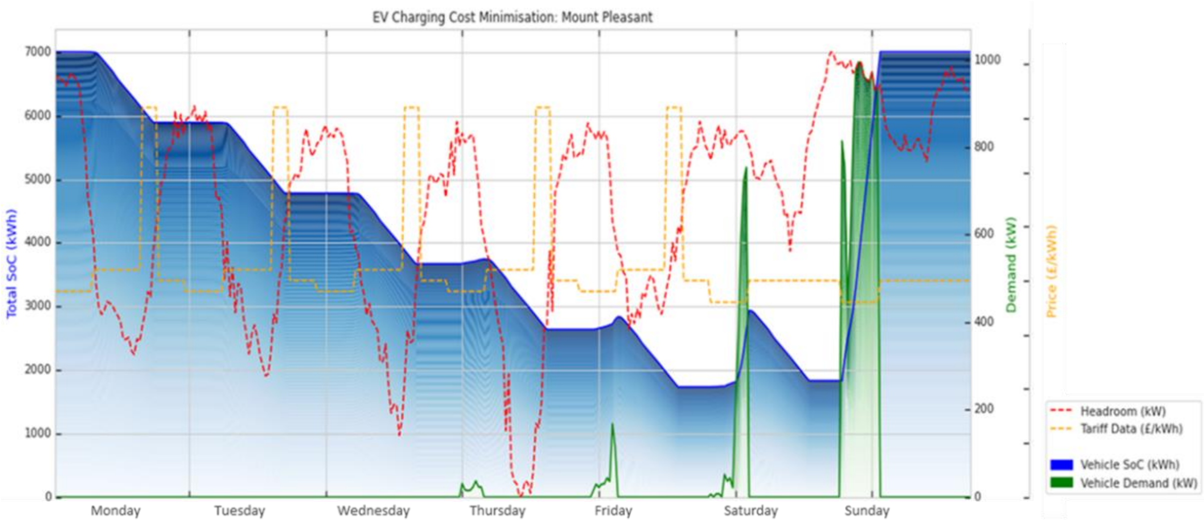


As Figure 17 displays, smart charging can minimise the site's power demand through management of charging. In this Mount Pleasant case, site operations could be carried out with a peak load 715 kVA lower than the existing ASC.

Using linear programming, it was possible to estimate a feasible charging schedule that could support EVs within the ASC, framing the problem as a minimisation problem with appropriate constraints. The objective function of the optimisation was written such that the schedule also aimed to avoid times when energy was more expensive. As a consequence, Royal Mail could have cheaper weekly energy bills, and the local DNO would benefit from the diversion of energy demand from peak times, the periods where they attribute a higher price per kWh.

Applying this simulation to Royal Mail's largest site, Mount Pleasant, it was found that vehicle charging could be managed within the available headroom (defined as the grid connection limit minus the power required for non-EV charging purposes), while only charging at the times when the electricity tariff was cheapest (Figure 18). On the graph the yellow line represents the cost of charging; the red line the site's headroom and the blue area the combined charge of the vehicles at the site. The green line represents charging activity, where it has been timed to occur when the vehicles are at the depot, at the times of lowest power prices and within the available headroom, successfully returning the charge of the vehicles to the same level as at the beginning of the week.

Figure 18 – The simulated site headroom relative to the ASC for Mount Pleasant, plotted alongside the vehicles' State of Charge (SoC) and the varying price of electricity (Tariff Data)



3.6.3.3 Analysis of connection cost implications

A sample of 20 Royal Mail depots were analysed with the project's depot planning model in order to ascertain the peak load from current electrification plans and potential future full-depot electrification. Three cases were modelled for each depot:

- The **base** case where all CPs are used at once at the time of peak load;
- an **unmanaged** case where vehicles are charged at the maximum possible rate as soon as they return to the depot,
- and a **smart** charging case where charging times and speeds were flexed to fit under the ASC or, if this was not possible, exceed it by the smallest possible margin.

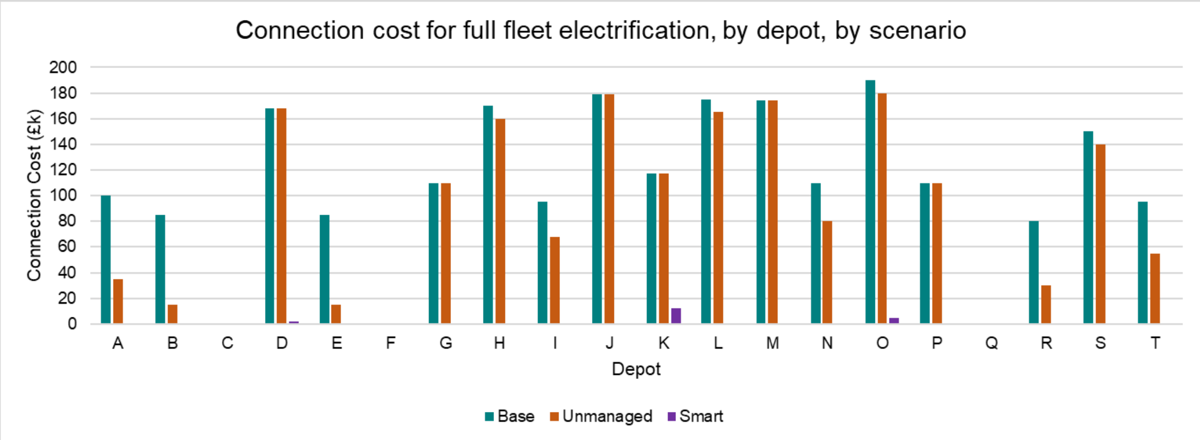
The resulting loads were assessed by UK Power Networks' connections team to obtain an estimate of the connection cost for each scenario. It should be noted that this was an estimate based on a desk-based exercise and not a full quote, as detailed site surveys were not carried out. The result of this is shown in Figure 19.

In the base case, 17 of the 20 depots required some form of connection upgrade to enable site electrification, with estimates in the range of £80,000 to £190,000 per site. In the unmanaged charging case all 17 would also need upgrades, but the costs of some sites were lower, ranging from £15,000 to £180,000. The smart charging case demonstrated a significant reduction in connection costs – most depots could charge within their existing ASC if smart charging was used to reduce peak demand, with only three sites requiring minor (£2,000 - £12,000) upgrades. While the cost of connections is site dependent and difficult to predict, this initial sample shows a significant potential benefit to the connecting customer of smart charging.

The time connect was also considered for a number of depots. The maximum timescale in the base case was between 6-12 months, whereas in the smart charging scenario this was cut to

12-14 weeks, with the majority of the depots not requiring a lead time for an upgraded connection.

Figure 19 – Connection cost estimates by depot and scenario



3.6.4 Profiled connections

Profiled connections are a proposed new type of connection product where the DNO and customer can agree to a connection profile that can vary in 30 minute blocks across the day. This allows a profile to be negotiated that matches the power demand of the customer with local network constraints, allowing more customers to connect before upgrades to network infrastructure are needed.

Early work related to profiled connections focused on analysis of the Royal Mail sites to identify the potential to reliably maintain a profiled connection. The work built on the earlier analysis of smart charging schedules and the logic of the depot electrification models to define potential profiled connections for each site.

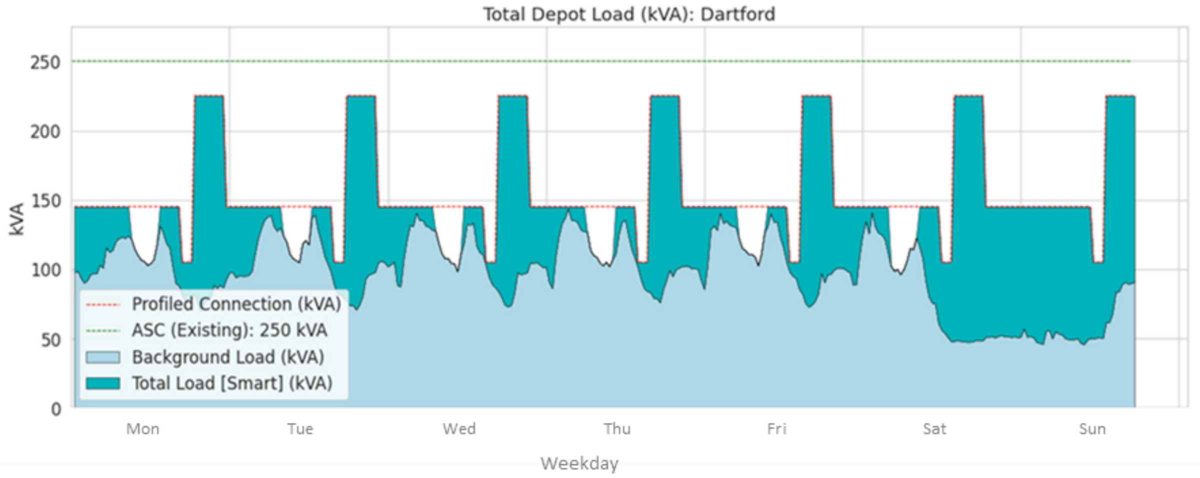
The profiled connections were established using three primary foundations of logic:

- Days were split into three "time blocks" per day: the time block of constraint and then the two periods either side of it.
- Each time block in each profiled connection has the lowest capacity (kVA) that could be adhered to during the simulation.
- Rules-based business logic simulated the charging load.
    - For example, using a certain smart charging policy, and ensuring that vehicles never drop below 20% SoC.

For the purposes of the trials, profiled connections are planned as pseudo profiled connections, whereby the new profile would be imposed below the existing connection agreement (Authorised Supply Capacity, ASC). This was required to mitigate the risk of an eventual breach in profiled connection limit resulting in damage to network equipment, while maintaining ability to explore the extent to which EV charging could be managed within a variable connection limit.

Taking the time of network constraint as an input, 5pm to 7pm in the case of Dartford, the model showed that load could be minimised at this time of day, by increasing at other times of day. A pseudo profiled connection was developed, with three limits per day as shown by the red dotted line in Figure 20.

Figure 20 – The simulated profiled connection for Dartford, and the time-block segmentation and associated capacity



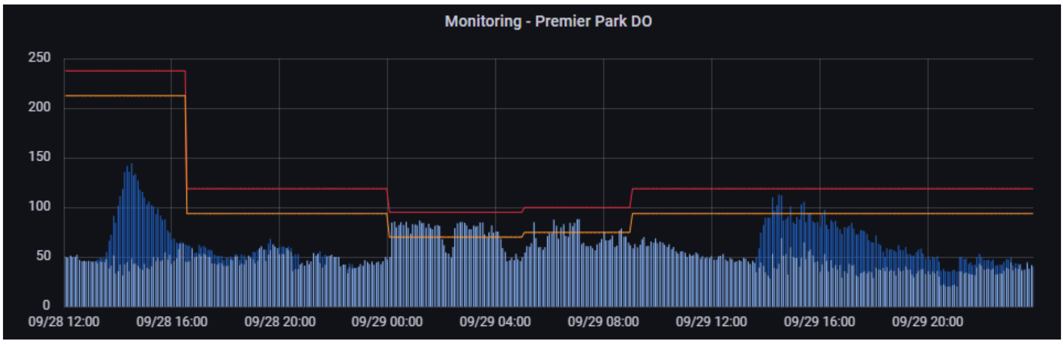
Profiled Connection: Dartford			
Time Block	Start Time	End Time	Capacity (kVA)
1	00:00	17:00	145
2	17:00	19:00	105
3	19:00	00:00	225

This approach will be developed further in subsequent profiled connection experiment runs, using more granular network constraint data as an input to create a profile varying up to 48 times per day.

Following the development of the proposed profiled connections, they are currently being trialled at each of the depots, by entering the profiled connection into the depot optimisation system so that EV charging is managed to keep total site demand below the profiled connection.

While full analysis of the initial results is still ongoing, initial observations have been encouraging. Figure 21 shows the demand at Premier Park Depot before and after the imposition of a profiled connection. The light blue bars show uncontrollable background demand and the dark blue bars controllable EV demand. The red line is the connection limit imposed on the site and the orange line is a target limit the system is trying to maintain load to. As can be seen, the day on the left of the chart, with no profiled connection in place results in a much higher peak demand than the day on the right side of the chart, where demand is spread out.

Figure 21 – Profiled connection at Premier Park depot



At some locations, for example where EV charging makes up a small proportion of overall load or where there are unpredictable patterns of background load, profiled connections may be viable as a means of freeing up network capacity, but it may be more difficult for the control of EVs to actively ensure compliance with profiled connections. This is because the variability in the background load can be greater than the change that can be achieved though control of EVs.

Ongoing experiments and analysis are looking at the effectiveness of profiled connections, and the use of EV charging management to maintain them, at depots with a range of different EV populations.

3.6.5 Flexibility

With the simulated profiled connections indicating that smart charging could help support electrification of fleets within current electrical capacities of the Royal Mail sites, the trials then investigated the extent to which smart charging could alleviate constraint on the grid dynamically in response to flexibility requests. The distribution network may need to limit supply at designated times in response to occasional anticipated spikes in demand, and so could request local energy consumers to temporarily suppress their energy demand to mitigate the peak. This allows the DNO to avoid network reinforcements and keep costs down for all network customers. Providing this flexibility for the distribution network, by adjusting the charge schedule in response to these requests, would provide value for Royal Mail – since it can be monetised – and would benefit the network operator's customers as easing spikes in demand or capacity constraints may provide a more cost-effective option than building new network infrastructure. Optimise Prime is exploring seven flexibility parameters through the trials, as shown in Table 20.

Table 20 - Flexibility Parameters

Parameter	Learnings to date / Future plans
Cost: At what value (£/kW/h) is it economical for fleets and PHV operators to provide flexibility services? How does the response quantity/quality vary with price?	The initial trials have calculated a basic price for flexibility using a calculation based on several factors. In general, responding to flex results in a lower power cost, as in most circumstances businesses are asked to flex from high-cost times. Larger volumes of flex are likely to be cheaper (in terms of £/kW/h) due to the fixed costs of responding to events
Magnitude: What is the aggregated total amount of load (kW) that can provide flexibility services for a given type or number of EVs?	Over time the trials will assess offering different proportions of the charging load. Initial trials have identified that predicting the controllable load at any time is key to increasing magnitude. The vehicles used also impacts magnitude, as charge speeds differ. The project is focusing on improving these predictions and the proportion of the load that can be controlled.
Duration: How long (hours) can this flexibility service be sustained for?	Trials have so far focussed on short (1-2 hour) flexibility periods and this will be varied in future trials.
Responsiveness: How quickly (days, hours, minutes) can commercial EVs respond to take part in flexibility activities?	In the WS2 trial, initially assets were dispatched at the time flexibility was requested for. This was found to be unreliable, as it could take a short time for the setpoints to be enacted. The timing has been adjusted to initialise the setpoint change 15 minutes before the required time and this appears to be ensuring the load changes by the time the flexibility event begins.
Proximity: How does the response or cost vary with the length of notice given to the fleet or PHV operator?	The three flex products (A, B and C) will test the response from month-ahead, day-ahead and intraday bids across WS1 and WS2. To date we have identified issues with accurately predicting load in both products A and B – comparative performance will be studied as the trial progresses.
Make-up: Is there a variation between availability and utilisation payment values that delivers the lowest service cost?	Product A includes separate availability and utilisation payments. Future activities will consider the optimum balance given the costs of flexibility provision.
Predictability: How predictable is the flexibility from commercial fleets and PHV operators? Can it be relied upon to deliver when requested by the DNO?	Initial trials have highlighted the importance of accurately predicting load in order to make bids and deliver flexibility. While flexibility has been delivered, the baseline has not always followed what was predicted and improving the predictions will be a future priority for the project. This is discussed further in Section 3.6.5.2

3.6.5.1 Modelling Flexibility

The trials built a model to simulate availability considering both flat connection agreements (characterised by unmanaged charge schedules) and profiled connections (underpinned by smart charging). Key learning objectives for the exercise were to:

- Predict trends in flexibility availability/cost given the simulated connection types (flat or profiled), as well as considering the time of day/month.

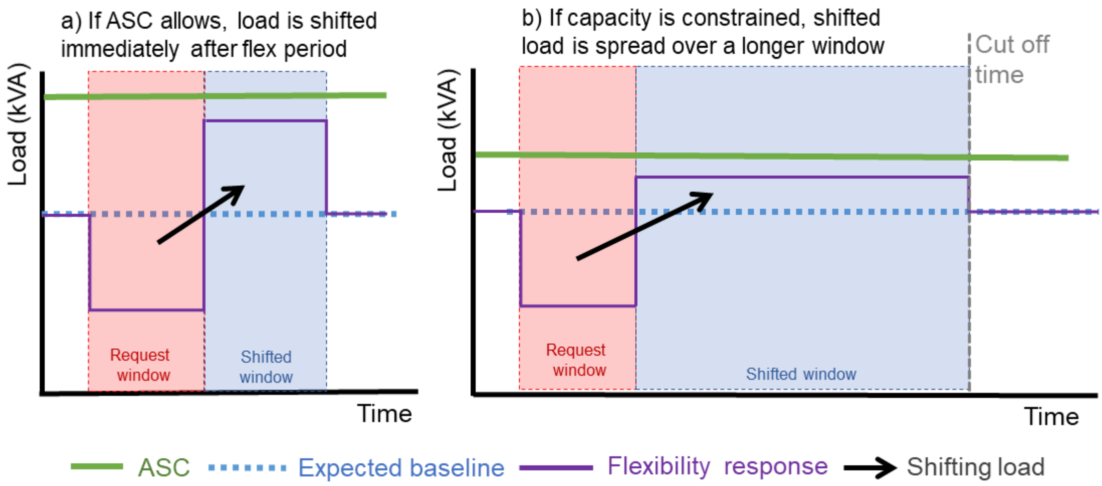
- Determine patterns in flexibility availability/cost.
- Evaluate predictive capabilities for depot flexibility over different time scales, for example how long before the fact could flexibility availability be accurately predicted.

The model supported two modes of flexibility, as shown in Figure 22:

a) Shifting demand from a request window to a “shifted window” of the same length, commencing immediately after the request window.
b) Spreading the demand from the request window to a “shifted window” of a potentially different length to the request window, up to a determined cut-off time.

A flexibility request would be accepted if the demand could be turned down and transplanted to the shifted window. A request would be rejected if either the CP demand could not be reduced in the request window, or if the extra load added to the shifted window exceeded the ASC of that depot.

Figure 22 – Flexibility model modes



The model was applied to example scenarios to test and demonstrate the logic. In the successful example (Figure 23), the CP load – the purple line – quickly drops from the predicted load (the blue line) to fulfil the request (during the red shaded period), and then spikes at the termination of the request window to recover the charge that was deferred (during the blue shaded period). At all times the predicted charging power is above zero and the site load is below the ASC.

Figure 23 – Example of an accepted flexibility request

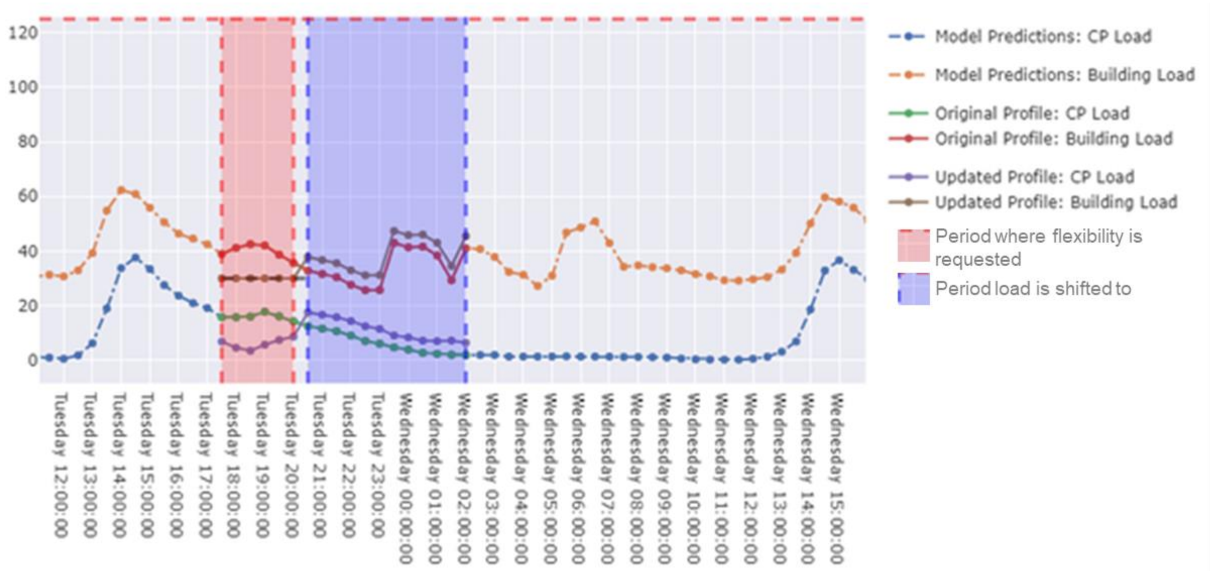
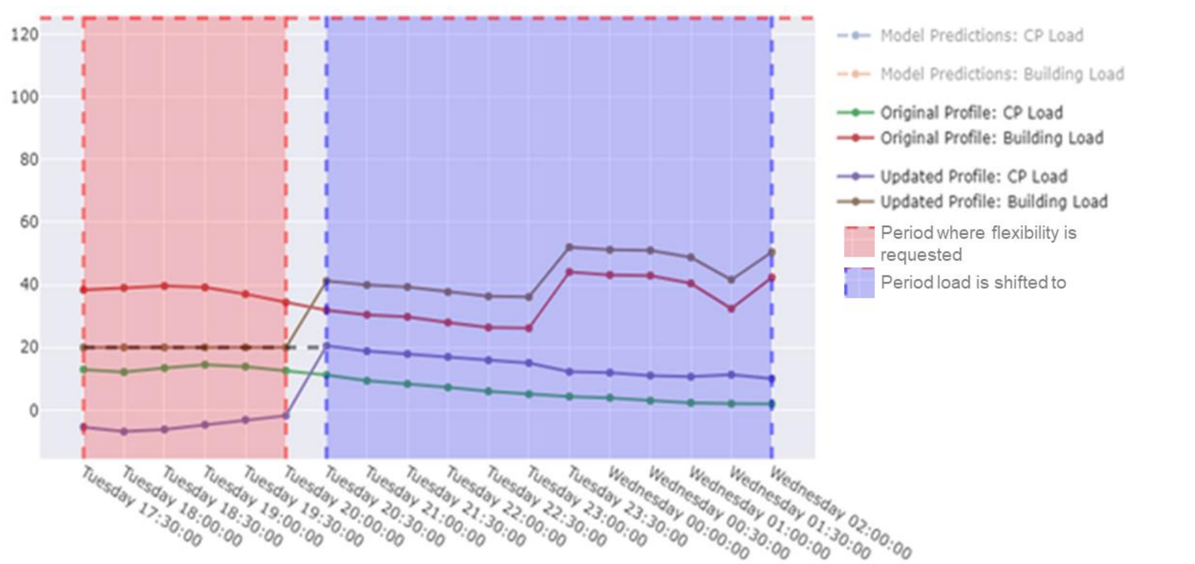


Figure 24 shows and unsuccessful example of a flexibility request. In this example, the CP load is predicted to be lower than the flexibility requested and in order to fulfil the request the modelled CP load (the purple line) would have to decrease to below 0, and consequently the request was rejected.

Figure 24 – Rejected request, illustrating the CP load would have to drop below 0 to satisfy the suppression demands of the flexibility request



The trials are currently investigating this practically on the Royal Mail depots, using the logic and experience gained from the conceptual work here. To do this, UK Power Networks are tendering for flexibility from the Royal Mail depots in two products: A (forward option) and B (day ahead spot), described in Table 21. The feasibility of providing flexibility will be analysed to create a bid (a month ahead for Product A and Day ahead for product B) and, provided the bid is successful, flexibility will be dispatched and a settlement process run to verify whether delivery was successful. Throughout the trials a range of different volumes and durations of flexibility will be requested to test the capabilities of the sites.

Table 21 – Optimise Prime flexibility products A and B

ID	A	B
Product	Firm Forward Option	Spot Auction
Timescale	Forward (months to years ahead)	Spot (Day-Ahead or Intra-Day)
Procurement	Tender	Auction Standardised bids
Market clearing	Pay-as-bid	Pay-as-clear
Dispatch	Operational timescales Partial dispatch	Scheduled at auction award
Baseline	Recent history Last Observation	Forward schedule OR Recent history Last observation
Payment	Availability and Utilisation	Utilisation

3.6.5.2 Flexibility results

During August 2021 the trials ran the first series of flexibility events. One of these between 23 August 2021 and 5 September 2021 was focused on testing a simple, large turndown request on weekdays, and was run as a test of Product A. This test occurred across three depots: Dartford, Mount Pleasant and Premier Park.

Outline of test:

- Bid 80% turndown against expected load
- Weekdays only
- 15:00 – 18:00 local time (BST)

The aim of this trial was to test the maximum flexibility that could be delivered. 100% turndown was not tested as, in order to avoid disruption to Royal Mail operations in this stage of the trials, CPs are not turned down below 6A, and unrecognised EVs plugging into the depot infrastructure are not controlled. The expected load was predicted based on analysis of available demand on these days and times.

In response to a tender from UK Power Networks a bid was submitted in line with the rules for Product A, an example of this for Dartford is shown in Table 22.

Table 22 – Example tender response for product A flexibility

Bid Information	Values	Description
FU Reference	Dartford	The depot or (Flexibility Unit)
Day	Thursday	Day to execute the turndown
Flexible Capacity (kW)	22	Amount in kW to be turned down below the expected EV load
Maximum Run Time (hours)	3	Total hours for the turndown to last

Recovery Time (min)	1,440	Minutes post turndown for the total energy to be recovered
Response Time (min)	30	Minimum minutes before the turndown required for the DNO to request a turndown
Availability Fee (£/MW/h)	11	Fee paid to flexibility unit for flexible capacity being available (whether it is utilised or not)
Utilisation Fee (£/MWh)	174	Fee paid to flexibility unit for flexible capacity being utilised

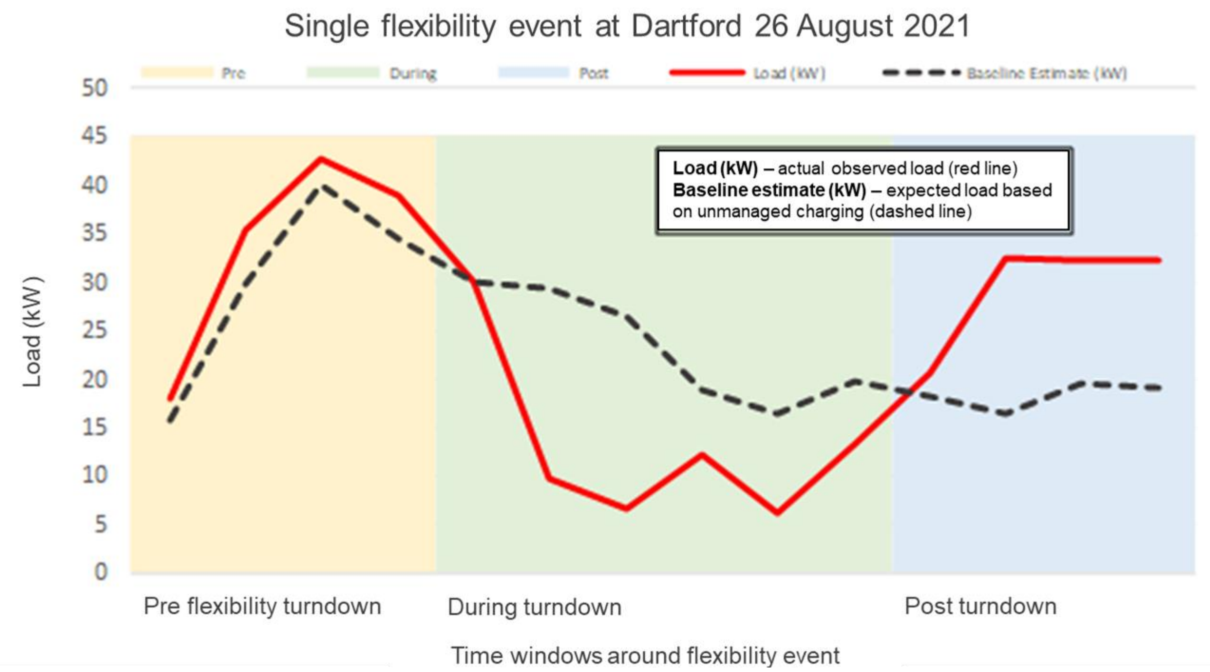
Once this bid is accepted by the DNO, the DNO can then send a dispatch to the system controlling the EV load. The dispatch sets the level of flexible capacity to be provided during a pre-agreed window, within the limits set out in the bid. Taking the example of a Monday at Dartford, a turndown dispatch can be seen in Table 23.

When the flexibility event is enacted the charging system attempts to reduce EV load at the depot by the flexible capacity requested in the dispatch message. A single day's example of this can be seen in Figure 25 for Dartford on 26 August 2021. It's clear to see pre-flexibility the load per 30-minute Programme Time Unit (PTU) was close to the expected baseline, showing that in this event the forecast was accurate. During the flexibility event a clear reduction can be seen against the previous measurements and the predicted baseline. There is also a higher than predicted load in the following periods as load increases to offset the flexibility provided.

Table 23 – Example of a Product A dispatch request

26/08/2021	Flexible downturn requested in kW
15:00	22
15:30	22
16:00	22
16:30	22
17:00	22
17:30	22

Figure 25 – Results of a single flexibility event at Dartford



The initial trials of flexibility have been generally successful in demonstrating the ability of the fleets to provide flexibility, they did highlight a number of issues that needed to be addressed:

- The effectiveness of the ahead of time base lining varied by site, and in some cases the load at time of delivery was higher than what was predicted, for example due to the addition of new vehicles or other loads. The project will continue to look at the impact of these changes on the ability to deliver flexibility as requested. This is explored further in Section 3.6.5.3.
- Due to the limitations put in place on which vehicles would be charged, there were a number of vehicles at some depots that were not actively controlled (for example vehicles that hadn't identified through a known RFID card). The minimum charge speed also impacted the change of rate differently, in percentage terms, depending on the vehicle being charged. As a result the 80% target for EV load reduction was not achieved. Future trials will take into account more data regarding controllable charge when calculating flexibility bids.
- It was noticed that the system was reducing demand after the start of the turndown period, rather than ensuring the change had started before the turndown period begins. The timing of the flexibility turndown has been altered, with assets dispatched 15 minutes prior to the flex period start, to better respect the requirements of the product in future trial runs.

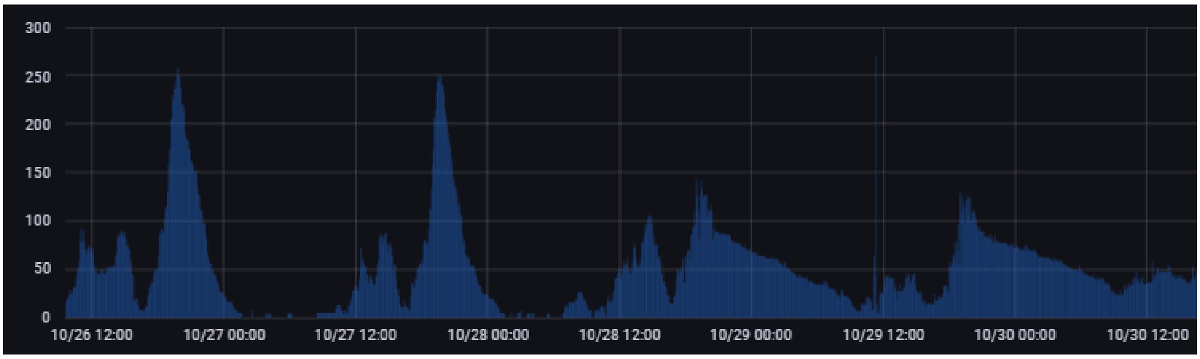
Testing of product B flexibility is at an earlier stage and as such limited analysis has been carried out on the performance of the assets. A test of the end-to-end bid and dispatch process for product B flexibility has been carried out at the Dartford depot and the resultant charging load is shown in Figure 26. In this test, a flexibility test was run where UK Power Networks was procuring a turndown from 16:00-18:00 of between 2 and 6 kW based on a submitted baseline.

As can be seen in the graph, the flexibility test resulted in a turn-down in instantaneous demand slightly larger than what was originally requested and it was maintained through the event. However, the actual load was higher than expected in the bid, both in terms of the baseline demand and the demand after the flexibility reduction. Work is ongoing to see how the accuracy of the forward baseline can be improved. As with flexibility product A, unrecognised vehicles which could not be controlled limited the ability to reduce the charging demand further.

Figure 26 – Product B flexibility test at Dartford (EV load in kW)

Subsequent flexibility trials have included an expanded number of depots and have been targeted to reduce peak load. The graph in Figure 27 shows the EV load at the Mount Pleasant Mail Centre over four days, the first two in an unmanaged mode and the following two providing product B flexibility. While there are still peaks in demand as vehicles plug in, the maximum demand is halved from 250 to 125kW, with the load spread throughout the night.

Figure 27 – Comparison of unmanaged demand and delivery of flexibility at the Mount Pleasant Mail Centre (EV load in kW)



3.6.5.3 Baselining

A key part of making a bid for the Optimise Prime flexibility products is baselining load – predicting what the charging load is at any time, and what proportion of this can be offered as flexibility.

The impact of inaccurate baselines varies by product. In Product A, performance is measured based on comparison to previous time periods, or previous days, so performance against precalculated baseline does not directly impact performance if the flexibility is delivered. However, inaccurate baselines can result in bids that cannot be realised, or potential flexibility that is not used. In Product B, a 24-hour baseline is submitted to the DNO as part of the bid, and ability to keep to the baseline is directly rewarded as part of the settlement methodology.

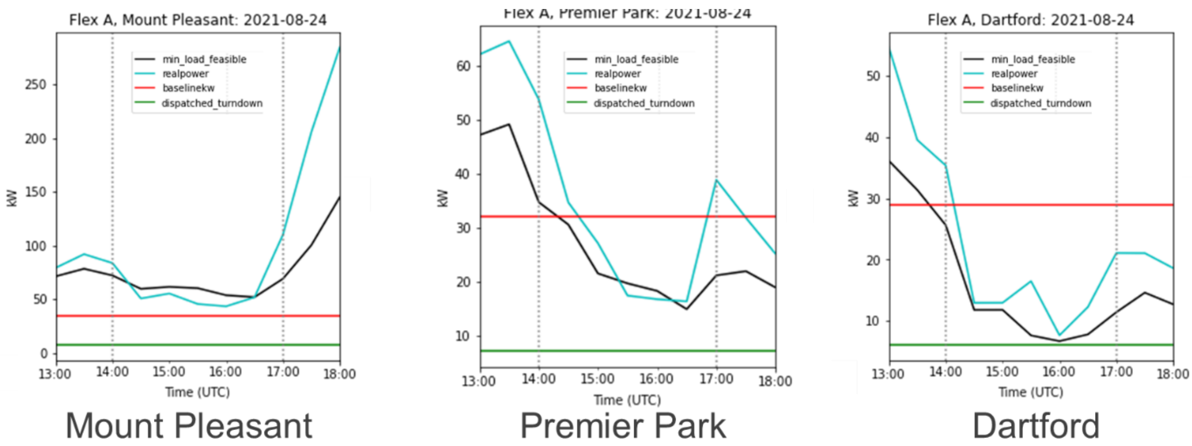
There are several factors that can impact on the ability to accurately baseline load:

- The predictability of EV use patterns – when EVs return to depot, plug in, and how much they need to charge on each day. For example, in the first Product A trial, Figure 28 shows the baseline demand used for the bid calculation a month ahead (the red line), it can be seen however that the actual load on the day (the blue line) was significantly higher across all three depots. As a result, although the decrease in load was generally achieved, the outcome was significantly above the predicted post-flex load (the green line).

- The trialling of different flexibility products and smart charging methods can make baselining more difficult. It may be necessary to go back further in time to model a baseline off normal load without other influences, and load patterns may have changed over this time.
- Ability to reduce charging demand, given that there are some limitations, such as vehicles that cannot be controlled and minimum charge rates.
- Some flexibility products require a static baseline over a period of time, but load varies
- The need to accommodate demand displaced by flexibility periods, given that whether the bid for any particular period is going to be accepted is not known at the time of the baselining.

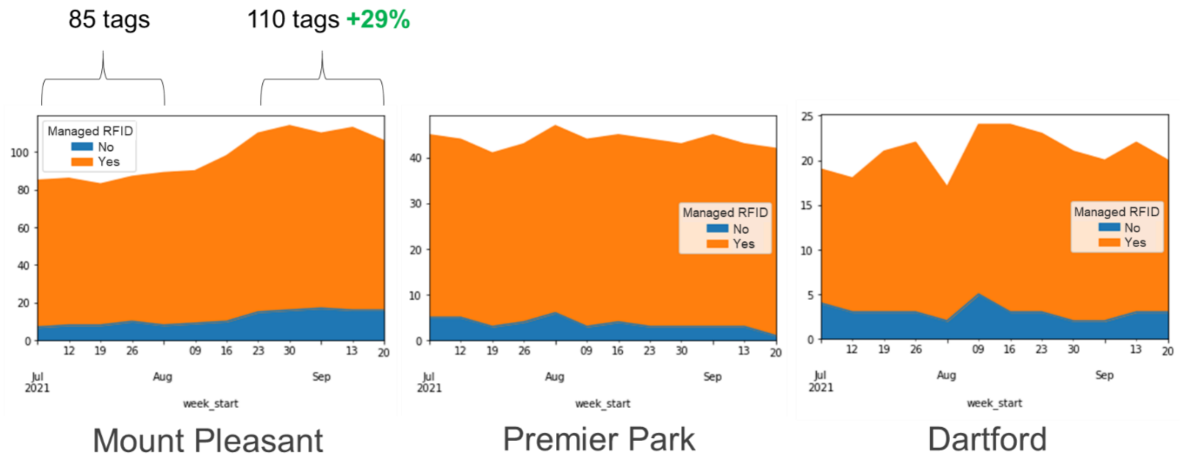
In Figure 28, the black line indicates what is calculated to be the minimum load achievable, given a) charge events that could not be controlled, and b) a minimum 6A (1.4kW) charge being provided to all controlled vehicles. As can be seen from the graph, the system was generally successful at reaching this minimum demand, but the minimum demand was significantly in excess of the pre-calculated baseline.

Figure 28 – Flexibility vs. Baseline



The main reason for non-controllable loads at Royal Mail sites is vehicles identifying with an unknown RFID tag. As shown in Figure 29, there is a proportion of charging events (around 10%) where the project systems do not recognise the RFID (shown in blue) and charging is not controlled. The number of RFID tags in use and the number of uncontrollable charge sessions varies over time, making accurate prediction of available flexibility more difficult.

Figure 29 – RFID tags used at Royal Mail Sites



Early predictions of the baseline were based on analysis of average electricity load over previous periods, however it has become clear that this alone is not adequate to produce an accurate result, as it did not account for changes over time in depot operations. Capacity for flexibility was also simply calculated as a percentage reduction in predicted load. Work is now ongoing to improve the baseline methodology, taking into account a wider range of factors, such as the varying number of vehicles charging, and to make a more accurate prediction of available flexibility. Changes have also been implemented to reduce the number of unrecognised charging sessions through improved management of vehicle RFIDs. The project may also consider the reduction of charging rates to zero on charge points, increasing the flexible load that can be made available, however the benefits of this need to be weighed against the risk of interruption to Royal Mail's operations.

3.7 Insights gained

The WS2 trials conducted at Royal Mail depots have begun to provide data that helps Optimise Prime meet the trial objectives. As with WS1, a more definite answer to the trial experiments will emerge once a longer EV charging dataset is available, but there is increasing confidence in the ability of the trials to meet the objectives.

3.7.1 Addressing the experiment hypotheses

RM_Ex_01 Initial hypothesis: The impact of unmanaged EV charging on Royal Mail depot electricity demand can be predicted using analysis of ICEV operation

The operational schedules of fleets have to be taken into account when electrifying as vehicle distance travelled and depot leave/return times are key when predicting EV energy requirements and charge point plug-in/plug-out times.

The Royal Mail operational schedules that were analysed varied from one depot to another, and varied depending on vehicle type (EVs/ICEVs).

As the trials progress more data will be collected allowing the project to compare these modelled operational schedules against the real-world performance of the EV, taking into account potential seasonal changes throughout the year.

RM_Ex_02 Initial hypothesis: The impact of 'smart' EV charging on Royal Mail depot electricity demand can be predicted using analysis of ICEV operation and unmanaged EV charging behaviour

The simulations of smart charging based on ICEV data showed that peak load minimisation and cost minimisation could be achieved at Royal Mail depots. The accuracy of these simulations will be modelled as further data becomes available from EV charging in each of the modes.

The modelling indicated that smart charging schedules could yield cost savings for Royal Mail and other depot-based fleet operators by managing charging load to avoid peak energy cost times. The same technique should also alleviate pressure on the distribution network at times when it is most constrained.

In addition to reducing costs from peak energy usage, estimates of connection costs for the full electrification of several Royal Mail sites have been carried out. It was found that in all of the sites studied, connection costs could be avoided or significantly reduced if peak load was reduced through peak load minimisation based optimisation.

RM_Ex_04 Initial hypothesis: The load profile of Royal Mail depots can be predicted based on the degree of electrification of the fleet and charging mode adopted (unmanaged or 'smart')

As part of the modelling of different load scenarios for RM_Ex_01 and RM_Ex_02, expected load profiles have been produced for Royal Mail depots in different charging scenarios. These will be compared against actual results throughout the year to judge the accuracy of the predictions.

RM_Ex_06 Initial hypothesis: The need for network reinforcement resulting from depot fleet electrification can be mitigated through profiled connections

Profiled connections have been simulated and trialled at the Royal Mail sites. Initial trials of the profiled connection systems are at an early stage but have shown that it is possible to control overall load in line with a profile at some sites through the use of EVs. There is likely to be a need for a minimum volume of EV load, in proportion to background site load, for the EV load to be able to be controlled without background load breaching the profile.

Future work in this area will look at the cost (and potential savings) of providing profiled connections and the impact of this on the connecting customer and the DNO, in addition to continuing to revise and test different profiled connection scenarios at the sites, such as more granular and varying profiles.

RM_Ex_16 Initial hypothesis: The availability for depot based EVs to be utilised for flexibility services can be predicted from 'smart' and unmanaged charging experiments

Smart charging has the potential to facilitate participation in flexibility markets which could provide even greater value to the network operator by adapting the charge schedule to accommodate dynamic requests to turn down energy usage. Initial trials have shown an ability to deliver flexibility on demand from EV charging at Royal Mail depots based on dispatches from the DNO.

The tests did however highlight some issues that may affect the reliability of depot demand response, such as the limited predictability of vehicles at some locations, and reliance on authentication of vehicles to provide demand response in the trial method. Further trials will continue to quantify these issues and consider potential solutions to maximise availability of flexibility.

3.7.2 Other learnings

In addition to the learnings that directly address the trial hypotheses Optimise Prime has generated a number of learnings from trialling depot charging in WS2:

- **Complexity of measuring load at some sites**: While initial testing had indicated that the project was fully monitoring load at all sites in the trials, once the trials began it became apparent at one site that this was not the case, as EV charging demand was occasionally exceeding total site demand. Investigations on site with the load monitoring contractor found that the initial monitoring installation had not considered all transformers in the site's complex electrical installation and some EV-related charge was being missed. In this particular installation it had not been possible to install monitoring on the main feed without powering down the site, so multiple sensors had to be installed on cables feeding different loads within the building and it was difficult to identify which cables were relevant to which loads on the site. Further sensors were installed to ensure all relevant load was monitored. This incident further emphasises the learnings in Deliverable D3, that on older and larger sites fully measuring load can be a complicated and lengthy process for which sufficient time and resources needs to be allowed.
- **Difficulty of network side load monitoring on the LV network**: The project identified VisNet Hub as the load monitoring system that the DNO will use to monitor compliance with profiled connections. This system interfaces with the ANM system and appears to perform well. However, it has become apparent that it is not always possible to install this infrastructure within the DNO estate, and that installing at customer premises can be complex and time consuming for the DNO. Specifically within Optimise Prime there have been issues with space constraints, managing asbestos, negotiating legal agreements and separating tasks that need to be carried out by the DNO and the customer's contractors. An alternative means of monitoring compliance may be needed, such as requiring the customer to install a suitable system, and this will be considered.
- **Using RFID as a means to identify vehicles**: As raised in Deliverable D3, during the testing phase it was found that using RFID authentication to identify which vehicles were charging could be unreliable, as drivers do not always ensure that they authenticate with the RFID assigned to their vehicle. There are a number of reasons for this, such as some vehicles having two RFIDs for different CPs, use of master keys to start multiple charge stations, and new RFIDs being supplied without the knowledge of the project team. This reduces the number of vehicles that can be controlled in the current system design. The project is now adding new RFIDs to the system when they are seen and is taking steps to reconcile them with vehicles. Optimise Prime will consider whether further action is needed to improve RFID accuracy and may change the rules that define what loads can be controlled to overcome this issue without impacting on depot operations.

3.8 Next steps

The next activities on the Royal Mail trial will focus on improving the project's predictive modelling capabilities, based on analysis of the efficacy of the current models. Given the high volume of data being collected for CP and site load, it will be important to develop forecasting tools to facilitate the planning of profiled connections and of bids for flexibility events.

These events will be a key focus over the remainder of the trials period. Royal Mail EVs will participate in four periods of flexibility events of four weeks each. During these flexibility periods, the potential for Royal Mail EV charging load to be curtailed in response to signals from the DNO will be explored.

Similarly, four periods of profiled connection implementation are planned, during which the extent to which Royal Mail EVs are able to adhere to the behaviour expected from the simulations will be explored. The final profiled connection period will run concurrently with a flexibility period, providing insight into the potential trade-offs between the two approaches.

Alongside these trials, work will look at the commercial models associated with the trial methods, for both network customers and DNOs, and the behavioural issues associated with this EV transition. The first insights from this work will be presented in Deliverable D5.

3.9 Changes made or planned based on initial learnings

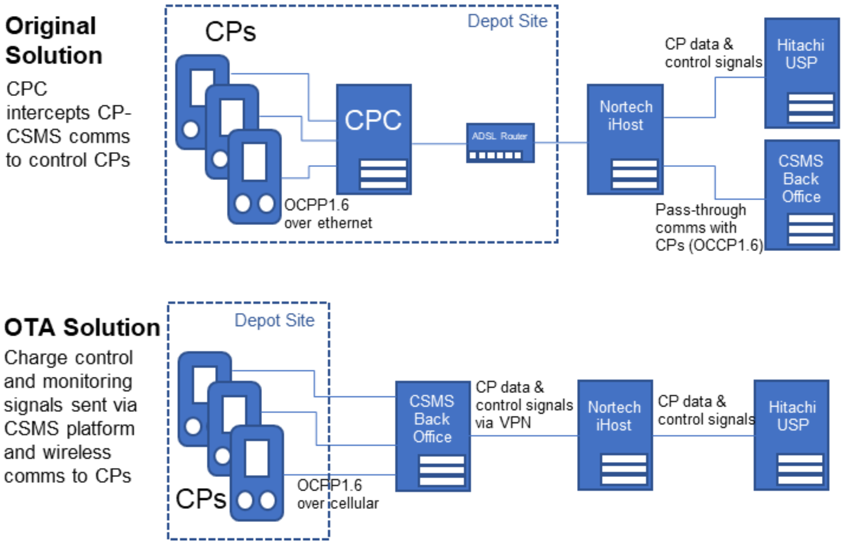
As the trials have progressed the project team have continued to evaluate the design of the trials and supporting systems in order to enhance the outcomes of the Optimise Prime Trials. Minor changes have been made to the trial design, other than the minor wording changes noted in Table 13, however there have been three further developments to the infrastructure used in WS2, namely:

Change to the communications infrastructure for CPs at some sites

In Deliverable D3 it was reported that an alternative communications infrastructure had been implemented – called Over-the-Air (OTA) – in order to add two additional electrified Royal Mail depots (Camden and Victoria) to the project without the need to install additional physical infrastructure at sites. This solution uses cellular communication via the CSMS backend platform to communicate with the trial systems, as shown in Figure 30, which is less intrusive and quicker to install than the wired solution.

Testing of this system was successful, and it was found that the OTA system solved an issue on the wired system where the second socket on older Swarco CPs could not always be controlled. As a result of this, it was decided to transition all Swarco chargers to OTA control, while the Alfen chargers remain controlled by the original physical infrastructure. This has resulted in the Victoria, Camden, Bexleyheath and Orpington depots being controlled by the OTA solution, Dartford, Islington Premier Park and Whitechapel having CPs controlled by both systems and Mount Pleasant being controlled by the original wired solution.

Figure 30 – Original wired and OTA charge management



Improvements to Panoramic Power infrastructure

Monitoring of the Panoramic Power (the site load monitoring solution used in the trials) infrastructure early in the trials identified that there were some variation in the reliability of site load readings. This particularly affected sites where bridges (devices that collect readings from individual sensors and communicate via cellular signal to the central system) were located in basements or equipment rooms with poor cellular coverage. Additional aerials have been installed at some sites and this appears to have rectified the issues. An extended period of monitoring is recommended to identify any potential issues with the connectivity of cellular devices.

Requirement for tooling to assist flexibility bid creation

Initial trials of flexibility products have shown that the calculation of the required baselines and offers for bids is a time-consuming process. In order to improve this process, additional tooling has been built by the project's data science team in order to automate this task. The tooling uses past load data and set parameters in order to return predicted available flexibility and a price, which can then be used to submit a bid. Automating this process is important for the future viability of the flexibility solution, as it would not be reasonable to expect customers to manually construct bids based on a large amount of information.

4 WS3 – Learnings from the Mixed Trials

4.1 Overview of the WS3 Trials

WS3 is the mixed charging trial, a data analysis exercise looking at the charging patterns and potential network impacts of PHVs. PHVs do not have a dedicated charging infrastructure and may charge at drivers' homes or at on-street or hub based public charging points. In Optimise Prime, journey data from EVs operating on the Uber platform in Greater London is being collected and analysed. This section focuses on the learnings gained from the implementation of the data ingestion (the process of capturing the data from a number of sources and storing it in a form that enables analysis), as well as from building and testing the models that are being used to analyse data during the trials.

4.2 WS3 Trial Experiments

The Uber objectives were split into nine experiments, as shown in Table 24. The core of work in WS3 has focussed to date on Ub_Ex_01 – estimating charging events based on trip data. The other experiments then utilise this data in their analysis. Where we note that an experiment is discussed in this report, a summary can be found in section 4.7.

Table 24 – WS3 Experiments

Experiment number	Hypothesis	Status
Ub_Ex_01	The time, location and magnitude of electric PHVs charge events can be estimated from Uber trip data	Discussed in this report
Ub_Ex_02	The time, location and magnitude of electric PHVs charge events will be influenced by external factors such as weather and large public events	Discussed in this report
Ub_Ex_03	Existing EV uptake models can be improved using data on actual uptake of electric PHVs within the trial	To be explored in deliverable D7
Ub_Ex_04	Locations lacking adequate charging infrastructure (current and future) can be inferred from Uber trip data	Discussed in this report
Ub_Ex_05	Electric PHVs charging causes low magnitude, local stress on the distribution network at present, but will pose a more significant threat in the next 10 years	Discussed in this report
Ub_Ex_06	DNO costs are unlikely to be affected by electric PHV charging in the short term	To be explored in deliverable D7
Ub_Ex_07	Electric PHV fleet operators are unlikely to be significant flexibility providers	To be explored in deliverable D7
Ub_Ex_08	The value available from flexibility provision is insufficient to alter driver behaviour	To be explored in deliverable D7
UB_Ex_09	Charging infrastructure costs could be reduced using profiled connections across aggregated CPs	To be explored in deliverable D7

4.3 Status of the WS3 trials

The WS3 trials began in full in August 2020. At this point, the target number of 1,000 vehicles required for the trials was on the road, and systems had been put in place to capture and analyse vehicle trip data. This was earlier than for trials WS1 and WS2, due to the greater availability in the market of electric passenger cars, compared to vans, and the simpler technical solution needed to capture data from the vehicle journeys. Since this time, the size of the sample in WS3 has continued to increase, reaching 1,500 in February 2021 and now exceeding 4,000. Data capture in WS3 has continued beyond the originally planned one-year period and is expected to conclude in line with WS1 and WS2.

The workstream has progressed well, with significant learnings developed over the period. In order to analyse the Uber trip data, and complete the project objectives, the project team has built and run a number of models, re-running the models as more data has become available. This trial methodology is explained in the next section. Most of the models required to deliver the trials have been completed and the remainder of the trials period is planned to be used to refine learnings as the EV dataset grows with more drivers switching to EV, to further extend learnings by extrapolating results to expected future EV populations, and to model the impact of this growth on DNOs.

During the period the trial, and the preceding period when pre-trial activities were taking place, the COVID-19 pandemic, and the related restrictions on movement and activities has had an impact on the trials. Certain periods have been excluded from the analysis due to the disruption of travel caused lockdowns and the impact that would have on trip patterns. As a result of the global pandemic, data from March to May 2020 had to be excluded from analysis, and the trials had to expand considerably their use of historical data in order to minimise the skewing impact of the lockdown. The team have observed continued differences in trip patterns compared to pre-pandemic, such as considerably fewer trips to airports, resulting in reduced demand for some charging locations in West London.

4.4 WS3 trial methodology

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. This section describes how the project team has developed a number of models in order to do this.

4.4.1 Definitions and Profiles

Geographical Areas

Throughout the Uber analysis, Lower Layer Super Output Area (LSOAs) are used as the primary means of displaying geographic information. LSOAs are geographical units with roughly constant populations (between 1,000 and 3,000 people) contained within them, defined according to the 2011 census. In London, the average LSOA is 0.2km^2. Appendix 6.3 illustrates this with the borough of Newham as an example, showing how it is segregated into LSOAs according to population. London Boroughs are larger areas (excluding the City of London, populations range from 150,000 to 400,000 people) and are used where it was not possible to break data down to LSOA level or where fewer, larger areas make the data easier to interpret.

Defining Uber Data

The trials established defined rules to interpret the behaviour of Uber EV drivers seen through the trip data to ensure there could be standardised observations based on their behaviour. The following lists the definitions for interpreting driver behaviour:

- **Shift:** A period of time where a driver is using the Uber app with breaks no longer than four hours each (i.e. a new shift starts after a break of more than four hours). Additionally, if any resulting shifts are found to be more than 15 hours, they are divided using breaks of at least two hours to indicate a new shift.
- **Event:** A "log" in the Uber Trip dataset reflecting the vehicle status:
    - ***Open*****:** A driver is logged in to the Uber app, waiting for a trip.
    - ***En-route*****:** A driver has accepted a ride and is en-route to pick up a passenger.
    - ***On-trip*****:** A driver is on a trip with a passenger in the back of the vehicle. "On-trip" events are called "trips" in this report.
    - ***Offline*****:** *Artificially added to the dataset by Hitachi*. These events reflect moments where a driver is still on their shift but is not using the app. For example, the app might be turned off for a short break.
    - ***Off-shift*****:** *Artificially added to the dataset by Hitachi.* These events reflect times where the driver is not on a shift. For example, they might have gone home for the evening.

Classifying Trip and Vehicle Profiles

The trials classified trip and vehicles profiles to analyse any relationships between vehicle type and the type of trips undertaken by Uber EV drivers. Vehicle profiles were organised according to the range of the vehicle, which is displayed in Table 25 for the May-July 2021 period.

Table 25 – Vehicle profiles and the range brackets used to categorise them

Vehicle profile	Definition	Range (km)	Example vehicle	% of sample
Low	Range more than 1/6 lower than the median range	174-306	Nissan Leaf	45.8%
Medium	Range between 1/6 lower and 1/6 higher than the median	344-473	Volkswagen ID3	53.5%
High	Range more than 1/6 higher than the median	499-560	Tesla Model 3 Long Range	0.7%

Three trip profiles were classified according to the geographical characteristic of the end location: Inner city, Outer City, and Airport trips, with the following definitions:

- **Inner City**: Camden, City of London, Hackney, Hammersmith and Fulham, Haringey, Islington, Kensington and Chelsea, Lambeth, Lewisham, Newham, Southwark, Tower Hamlets, Wandsworth and Westminster.
- **Outer City**: all other London boroughs.
- **Airports**: City, Gatwick, Heathrow, Luton, Stansted and Southend.

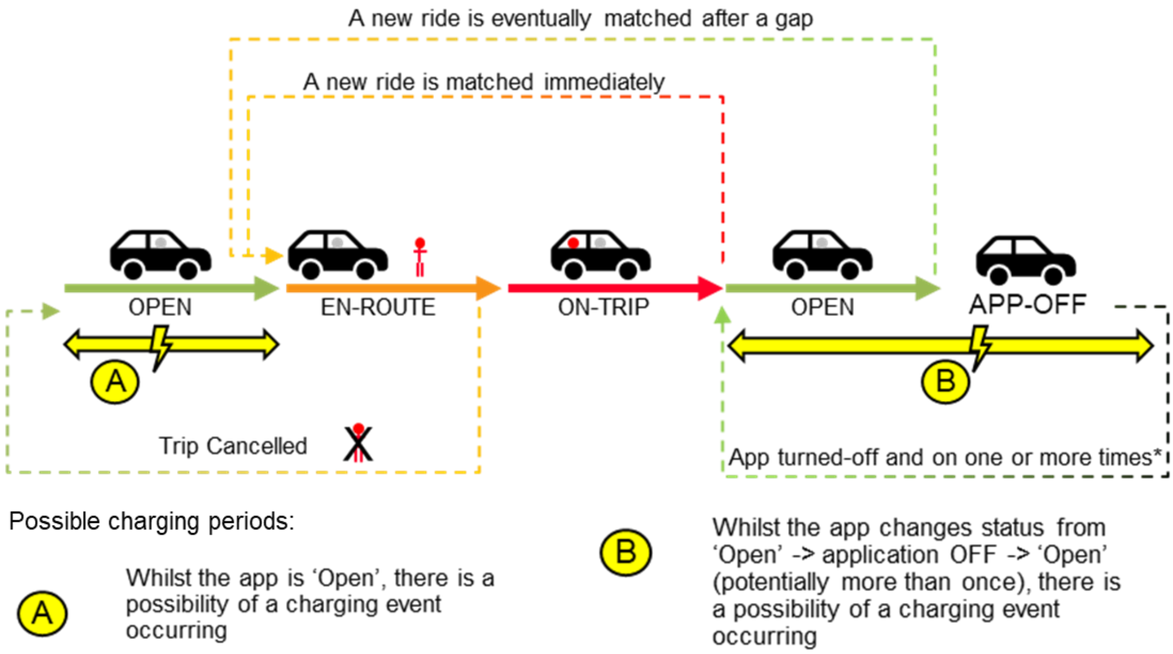
4.4.2 Inferring charging behaviour of Uber drivers

As the project does not know when Uber drivers charge, this has to be inferred from the distance they travel, gaps between journeys and a model of where charge points are located. Due to the scale of the analysis, involving many thousands of journeys, it is not possible to verify how close to reality these inferences are, however Uber drivers are taking part in a series of surveys looking at their views and behaviours regarding EVs and charging. The first results of this work will be presented in Deliverable D5.

4.4.2.1 On-shift charging: should, could, did charge

On-shift charging events occur during gaps between trips and other events (see Figure 31).

Figure 31 – Stages of Uber EV activity throughout the day, with A and B denoting when charge events could take place



In the absence of direct data on vehicle SoC, the trials developed a methodology to infer if a charge event occurred on-shift by evaluating if they:

- *Should* have charged
- C*ould* have charged
- And therefore *did* charge.

4.4.2.1.1 Should charge

To assess if a driver *should* charge, the trials used a probabilistic model based on their inferred SoC and the relative demand in their borough during their shift. If the inferred SoC was low, this was assumed to result in high range anxiety for the driver and therefore high probability they should charge and vice versa.

According to the model's assumptions on those two criteria, an 'S' value would be produced for each driver which denoted the extent to which they *should charge* (for a breakdown of how this was done see Appendix 6.4).

4.4.2.1.2 Could charge

Then, the trials would evaluate whether or not a driver *could have* charged. This was a deterministic {True, False} based on whether it was possible to drive along the road network using the shortest path (at the average road network speed) to the CP that would have given them the most charge in the time available on a chain of offline or open events, before returning to the next event in the Uber trip data. To discern this, the trials would check for each "open/offline event chain" (Figure 31).

4.4.2.1.3 Did charge

Following that, the Trials assigned probability scores, for whether or not the driver *did* charge, the D value. This was determined based on whether or not they *should* have charged and *could* have charged (the approach to this can be found in Appendix 6.5).

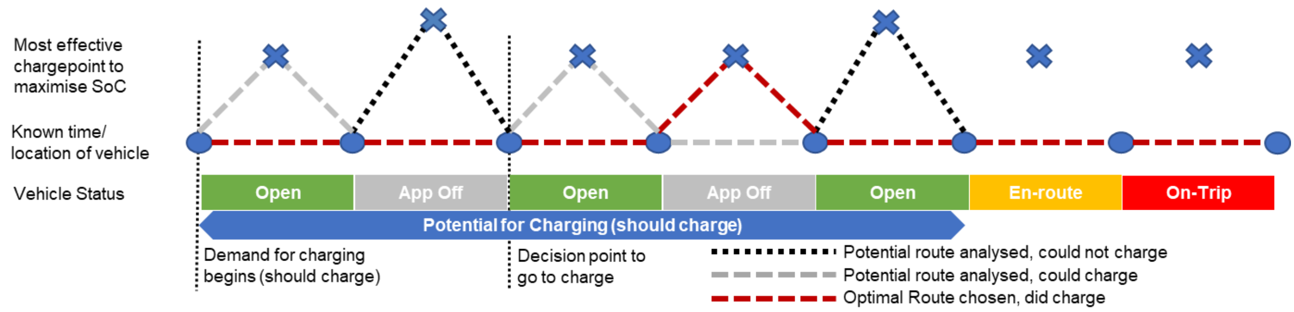
4.4.2.1.4 Summary of the approach

In summary, the following three concepts allowed the inference of whether a driver *did* charge:

a) The likelihood that they *should* charge.
b) Whether they *could* have realistically reached a CP.
c) The amount of charge they would have received from the CP.

Figure 32 visualises this.

Figure 32 – Overview of the *should, could and did charge* methodology to infer charging events in the absence of direct data



4.4.2.2 Inferring charging behaviour of Uber Drivers: Off-shift charging

Off-shift charge events were viewed to be instances where drivers were charging at the end of their shift, and this charge event did not precede another trip for at least four hours until a new shift was viewed to have commenced.

To infer off-shift charge events, the trials had to allocate vehicle 'home' locations at LSOA level for each driver. The 'home' locations were inferred from the frequency and distance of the LSOA at the start and end of driver shifts. For each vehicle, the trials attempted to find an LSOA that most frequently appeared in pairs as both the start and end LSOA for a driver's shift. These 'home' locations could be either boroughs or LSOAs. More detail on this can be found in Appendix 6.6.

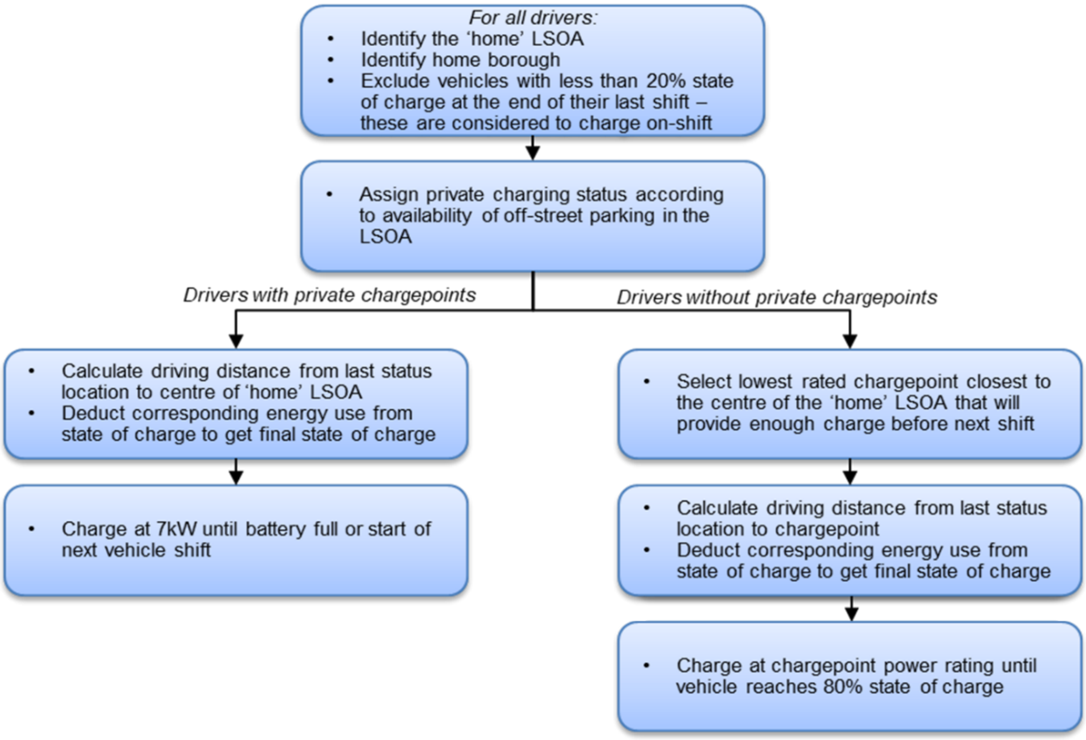
Since the time available to charge between shifts is much longer than for on-shift charging, the number of options for charging greatly increases; any public CP would be capable of delivering enough charge before the next shift began in most cases.

Having identified a 'home' location, drivers were assigned private charging status according to the availability of off-street parking in the borough. This was initially conducted using borough-level data from Transport for London (TfL) (Appendix 6.7), but on review it was considered that the variability of parking availability in boroughs was too high, so would not necessarily reflect the areas where Uber drivers lived. A study conducted by Field Dynamics (see Appendix 6.8) was identified that provided off street parking at LSOA level, so this data was used assign charging status. For the drivers assumed not to have access to off-street parking and therefore a private CP, Zap Map data was used to identify the most suitable public CP.

For those assigned to private CPs, the distance between the last status location to the centre of the 'home' LSOA was calculated and then the corresponding energy use to reach that location was deducted from the vehicle SoC. The driver would then be assumed to charge at 7 kW until the battery was full, or the next shift started.

Drivers deemed to be without private CPs would be assumed to select the lowest rated CP closest to the centre of the 'home' LSOA that could provide sufficient charge before the next shift. As was the case in analysing drivers with private CPs, the distance between the last status location and the CP was calculated, and the energy usage to reach it deduced. The driver was then assumed to charge at the CP rating until the vehicle reached 80% SoC (see Figure 33).

Figure 33 – How off-shift charging events were inferred



For both on and off-shift charge events, all inferences abided by a comprehensive list of business assumptions. They were as follows:

- The possibility of queueing to wait for an available CP was not considered

- Drivers were assumed to be rational and would therefore seek to gain the most charge possible in an event, assuming that they wanted to maximise their time on shift accepting Uber trips
- All drivers were therefore assumed to have 'perfect' information' about public CPs
- All CPs were assumed to be operational
- The monetary cost of charging was not considered, with the exception of the exclusion of some high-cost locations noted below
- Drivers were not modelled to be preferentially choosing specific CPs , for example due to personal preference, subscription services, or any other preference
- Concurrency of charging events was not considered. As a consequence, it was possible for a CPs to be over-utilised at certain times due to more drivers being assigned to it than there were available concurrent connections.

There was also a list of CP assumptions which shaped inferences on Uber EV charge events:

- The analysis conducted aggregated to a CP location level, rather than a specific CP level.
- All public CPs that were used were not restricted to the public nor reserved for certain vehicles, such as black cab taxis.
- CPs labelled "Workplace car park" were excluded from the analysis, following the assumption that these would be inaccessible for Uber drivers.
    - There was one exemption: a Tesla Supercharger location at the Royal Victoria Docks, since it is accessible 24/7 to the public.
- Certain vehicle brands were modelled to have access to certain, distinct locations:
    - Tesla EVs could access any Tesla location, and only Tesla EVs could access Tesla Supercharger locations. Additionally, Tesla EVs could benefit from the advanced speeds of Tesla Superchargers (120 kW not 100 kW), and Tesla Destinations (22 kW not 7 kW)
    - Vehicles could use dealership forecourt chargers, but only for dealerships of that vehicle make.
- CPs on Hotel/Accommodation or NHS property were included
- Q Parks were excluded from this analysis, due to their relatively prohibitively high cost of charging
    - Q Park on Park Lane was not excluded since from 14 October 2020 Uber had arranged for Uber drivers to have access to it.
- The charging speeds for the four CP types were as follows:
    - Slow = 3 kW
    - Fast = 7 kW
    - Rapid = 50 kW (DC)
    - Ultra-Rapid = 50 kW – except for Tesla EVs which charged at 100 kW, and 120 kW at Tesla Superchargers.
        - Since many EVs have limits on the power they can accept while charging, all vehicles using Ultra-rapids other than Teslas were capped at 50 kW.
- For off-shift charging, all private CPs were modelled to be 7 kW. All other assumptions for on-shift CP usage applied for off-shift.

4.4.2.3 Network Capacity

Varying levels of network capacity across London were calculated in order to discern where there was available capacity to further expand charging infrastructure, and where there were particular areas of network constraint.

To construct these visualisations, residual capacity was calculated for each LSOA by taking the maximum historical demand at the substation within the LSOA which had the highest 'headroom' between its maximum historical load and its rated capacity. Then, by applying the estimated kVA demand from inferred charge events, a 'worst case scenario' for residual capacity could be found and mapped-out for each LSOA. Since the exact time when substation's recorded historical maximum load occurred could not be pinpointed, the following assumptions were made:

- The trials assumed a worst-case scenario where the historical maximum coincided with the maximum half-hourly window for charging demand and all relevant EVs are charging concurrently
- All the charging events were assigned to the substation with the maximum headroom within the LSOA
- The historical maximum did not include these CP being active at the time
- LSOAs without headroom data are ignored
- The charging demand data is the maximum demand per LSOA

4.5 Data gathered

The WS3 trials utilise a number of different datasets in order to analyse the charging behaviour of the electric PHVs. The core data sets are sourced from Uber's platform and details the journeys taken by EVs in the Greater London area. This data is compiled monthly by Uber, anonymised and shared with Hitachi for analysis. When new vehicles are detected in the dataset, they are validated to ensure that each vehicle in the dataset is an EV.

In order to map demand against the constraints of the distribution network, datasets are captured from UK Power Networks and SSEN detailing the capacity and maximum observed demand at each of their substations in the study area. These files are updated quarterly, and substations where the capacity is reserved for a specific customer (and therefore will not be made available for charging) are excluded.

A number of commercial datasets are also used as part of the analysis. Principle among these is charge point location data, used to determine the locations where Uber electric PHVs can charge and at what speed. This data is licensed from Zap-Map and sourced periodically from their API. Weather, parking and geographic datasets are also used, as detailed in Table 26.

Table 26 – Datasets used in WS3

Data Name	Description	Use in Trial	Source
Uber EV Trip Data	Anonymised data for all EV trips taken in Central London, including trip status, start/end location and time, and vehicle make/model.	Used to understand driver behaviour, particularly in discovering where drivers SoC would be low and would require them to seek a CP.	Uber
Uber EV Vehicle Data	Details of which manufacturer and model EVs are used for which trip.	Facilitated analysis of trends of trip-type according to vehicle type.	Uber

Data Name	Description	Use in Trial	Source
EV Vehicle Range Data	Distances each EV make and model could travel before having to recharge	Enabled inferences on when and where Uber EV drivers would need to charge based on the distances they had driven since last recharging. Facilitated tracking of Uber EV vehicle range growth over time.	Multiple, publicly available third party sources. Worldwide Harmonised Light Vehicle Test Procedure used where available.
CP data	Comprehensive and accurate list of all publicly available EV CPs in London.	Used to support inferences of charge events by displaying where CPs are in relation to driver movements. Also enabled analysis of CP availability and proliferation across London.	Zap Map
DNO Substation Data	Low voltage (LV) substation location, rated capacity and historical maximum utilisation for London-based substations operated by UK Power Networks and SSEN.	Enabled analysis of the electricity network and its varying levels of capacity across London to satisfy Uber EV charging demand.	UK Power Networks SSEN
Weather Data	Detailed meteorological data, comprising: UV Index, Apparent Temperature, Humidity, Wind Speed and Precipitation Intensity, from November 2019 to June 2021.	Enabled comparisons between the impact of weather and the impact of time of day/year in influencing Uber EV trip demand and Uber EV battery SoC	Dark Sky
Area Segregation Data	Shapefiles of London Boroughs, middle Layer and Lower Layer Super Output Areas (MSOAs and LSOAs)	Enabled the clear separation of geographical areas of varying sizes.	UK Government Data
Off Street Parking Data	Per borough and per LSOA analysis of the proportion of homes with off-street parking	Enabled assumptions to be made with regards to the number of EVs using public infrastructure to charge	TfL, Field Dynamics

4.6 Analysis

This report summarises findings taken from data collected between November 2019 and April 2021, focusing on two primary phases of investigation: Phase 1 consisted of analysing Uber EV charging demand, and Phase 2 focused on understanding the impact of Uber EV charging demand on the low-voltage electricity network. Both phases involved varied experiments and streams of analysis.

In order to build a thorough understanding of Uber EV charging behaviour, Phase 1 included analysis on a number of data streams:

- Analysis was conducted on whether the types of trips drivers were fulfilling varied according to the type of EV they used
- Both on-shift and off-shift charging behaviours were investigated to identify where, when and how Uber drivers were recharging their vehicles
- The trials also examined patterns of CP utilisation across London, discovering where certain locations were experiencing burgeoning demand and, therefore, where infrastructural upgrades might be most valuable for drivers
- Across the data period, the trials tracked the impact of weather on battery use compared with time variables
- The growth of average vehicle range for Uber EVs and proliferation of the public CP network in London were also monitored.

In parallel, Phase 2 explored how Uber EV charging demand was impacting the electricity network in London:

- The trials consistently mapped the locations where there was ample network capacity to support an upgrade in the local charging infrastructure against the locations with the least capacity to absorb future demand
- This research manifested in regularly updated Red Amber Green (RAG) maps, as well as lists detailing the number of CPs that over-utilised locations could support to cope with aggregated demand there. This considered both on-shift and off-shift charging
- Finally, the general peak electricity load caused by Uber EV charging was tracked throughout the research period.

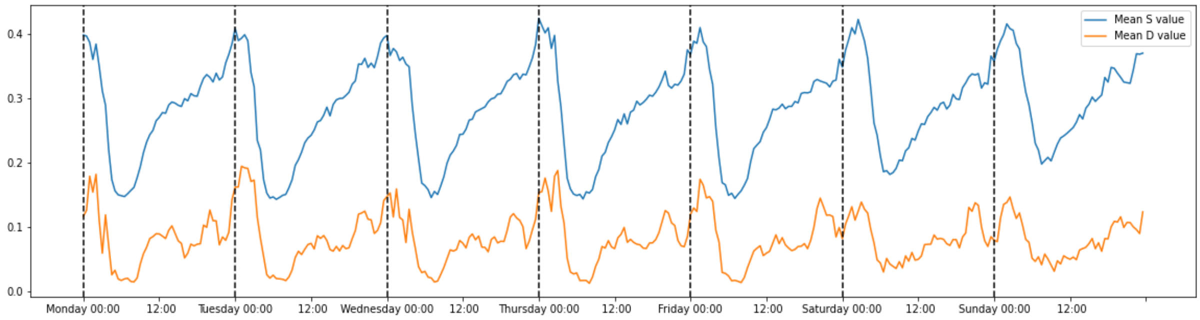
4.6.1 Phase 1

The Uber EV driver population was categorised into three groups according to vehicle range. Table 25 details the three groups and the range brackets used to segregate them. Early in the trial the low range bracket was dominant, with the majority of vehicles being Nissan Leafs, However, over time the average range has increased as Uber drivers have adopted new EVs with longer ranges.

The driver population was organised further according to their charging behaviour, for which there were two categories: on-shift charging and off-shift charging. On-shift charging was far less common compared to off-shift and this was consistent over the research period, although it did fluctuate slightly. The average percentage of those charging on-shift at the beginning of this period was 20.1% in June 2020, compared with 21% in June 2021, with it peaking at 24% in September 2020.

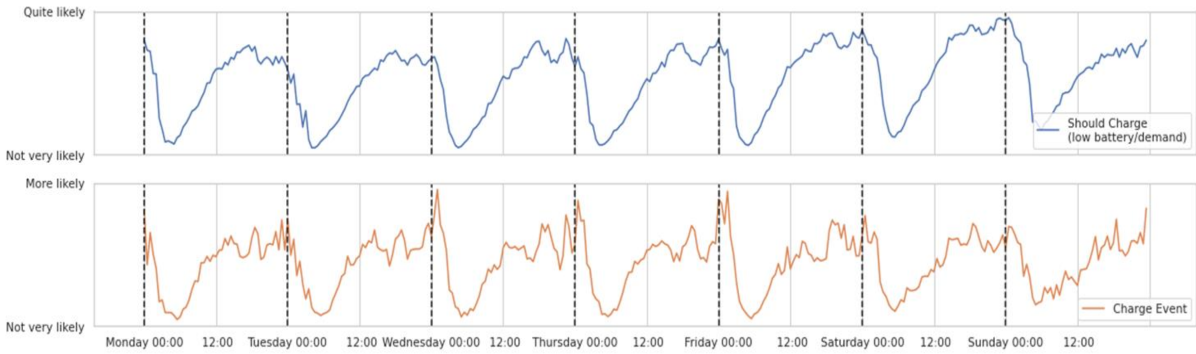
Those drivers that charge on-shift were least likely to charge in the early morning and in the morning rush hour period, from 04:00 to 09:00. Generally, as the vehicle SoC decreased, the probability of a driver requiring a charge increased, causing their calculated S value (the extent to which they *should* charge according to the conditions described above) to rise. However, there were also dips in the D value for Uber EV drivers (the extent to which the models assessed them as actually going to charge) during the evening. Reductions in the likelihood of Uber drivers charging during this rush hour period was most likely owing to high local trip demand encouraging drivers to keep accepting trips, deferring charging. Peak charging probability occurs late at night as SoC decreases and gaps between journeys are longer, making charging both feasible and more necessary (Figure 34).

Figure 34 – Visualisation of the probability that drivers *should* and *did* charge while on-shift over the course of a week. Based on data from November 2019 to February 2020



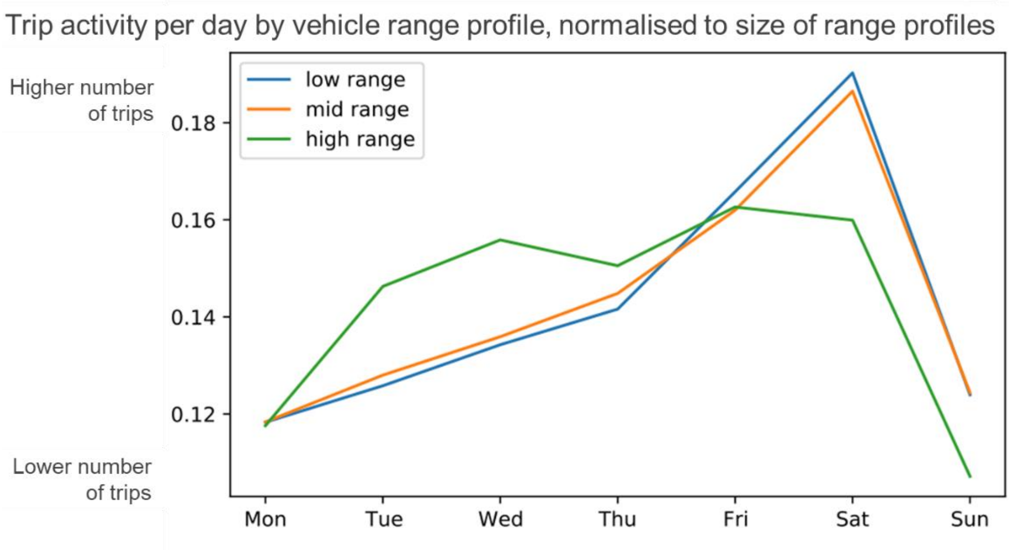
This trend remained largely consistent throughout the research period, however there were occasional minor changes. For example, from June to August 2020 Uber drivers exhibited more 'opportunistic' charging in the daytime throughout the working week, perhaps owing to a reduction in business travel demand releasing more time in the day for drivers to recharge. This is illustrated in Figure 35 where the afternoon periods saw much higher D values compared with what was seen from November 2019 to February 2020. On weekends, the D values rose in accordance with the later in the day it got.

Figure 35 – Visualisation of the probability that drivers *should* and *did* charge over the course of a week, based on data taken from June to August 2020



The Trials also distinguished differences in driver behaviour according to the vehicle they drove (see Table 25 for the vehicle type classes). Low and medium range vehicles seemed to fulfil very similar trip profiles. The only divergence between these two groups was low range vehicles were less likely to do airport runs, which was taken to be a symptom of range anxiety and low confidence in ability to top up charge near to the airports. High range vehicles were slightly less likely to operate at weekends (Figure 36), perhaps due to an increased likelihood of operating as part of Uber Exec or Lux categories and therefore serving a more business ridership.

Figure 36 – Uber EV trip activity according to vehicle range profile, based on data taken from May to July 2021



4.6.1.1 Understanding Charging Behaviour: On-shift charging

The trials sought to understand the charging patterns of Uber EV drivers, comprising the locations they charged at, the distances they travelled in order to charge, when they went to charge and the type of CP they then used. As detailed above, analysis on this was derived from the *should, could and therefore did'* charge logic.

So far, Optimise Prime has found that Uber EV demand for on-shift charging is most intense in Central London, particularly in the City of London and City of Westminster. Yet, both of these areas were two of the most under-served regions for Rapid and Ultra-rapid charging infrastructure. Drivers charging on-shift were generally forced to use Rapid and Ultrarapid CPs, since the time they had between trips was much shorter than if they were charging at the end or before their shift. This narrows their choices considerably, which was seen particularly in the early period of the research when there were very few CPs in Central London that were capable of delivering sufficient power in the small window they have to recharge. Not only did this force them to travel long distances to secure a charge, but the few Rapid and Ultrarapid CPs were operating beyond their capacity at times to support the burgeoning Uber EV demand in the central boroughs of the city.

In the early stages of the research, a charging hotspot also existed near Heathrow in the West owing to high airport trip demand (Figure 37). However, as the year progressed, this became less pronounced as demand aggregated even more around Central London. This is likely as a result of the reduction in air travel caused by the COVID-19 pandemic. By the end of the research period, a dominant proportion of the Top 10 most-utilised CPs in London were concentrated in the central regions of the city (Figure 38 and Table 27).

Figure 37 – Heatmap visualising the average D value – the probability that a driver did go to charge – for on-shift charging in LSOAs that accommodated more than 600 charge events. Data taken from November 2019 to February 2020

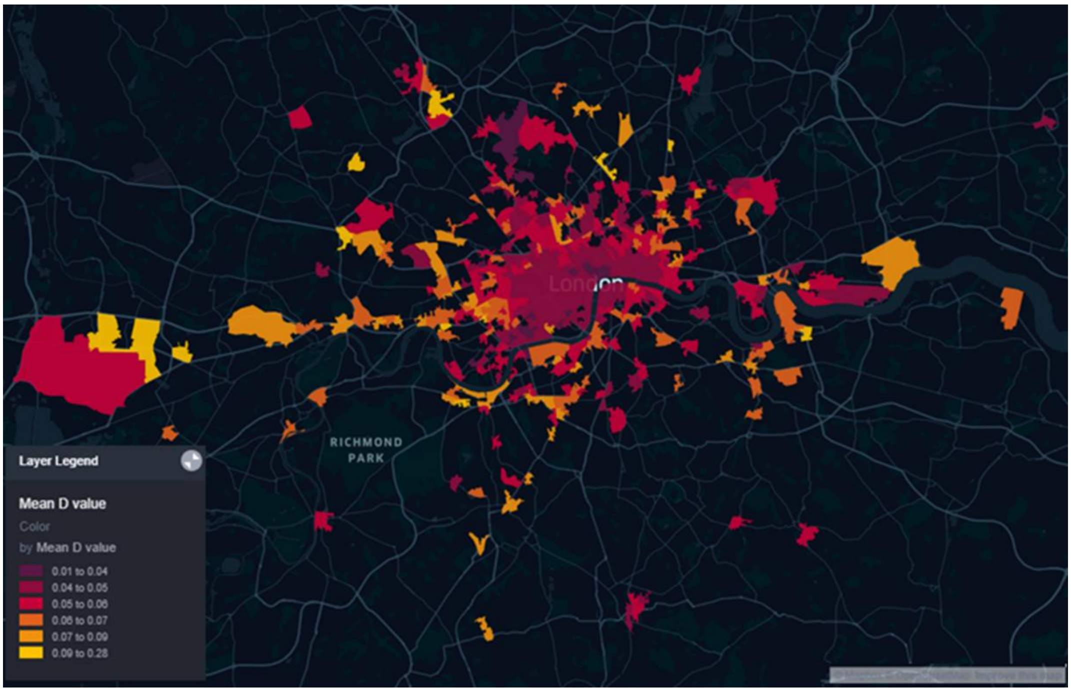


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Figure 38 – Heatmap visualising the number of charge events that occurred in each LSOA, with yellow bolts representing the location of Rapid and Ultra-rapid CPs, and red bolts indicating the Top 10 most-utilised CPs in the city. Data taken from February to April 2021

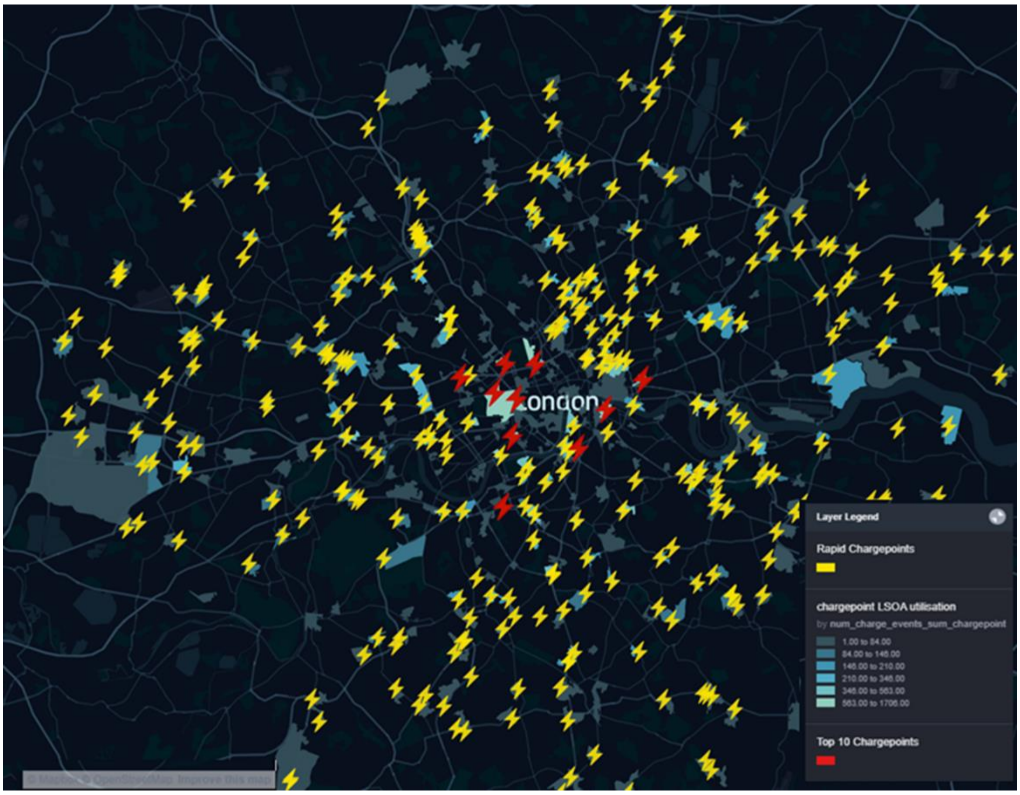

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Table 27 – The Top 10 most-utilised CPs. These locations are placed as the Red bolts in Figure 38. Data taken from February to April 2021

Chargepoint LSOA	LSOA description	Total Number of charge events in the LSOA	Average charge events per day	Other rapid/ ultrarapid chargers within 1 km radius
Camden 021B	Euston Osnaburgh	2,418	27.2	0
Southwark 002B	Borough Market / Southwark Street	2,023	22.7	0
Tower Hamlets 015D	Spitalfields	1,573	17.7	0
Westminster 019C	Park Lane	1,409	15.8	0
Lambeth 003A	Oval	1,305	14.7	2
Kensington and Chelsea 012C	Sloane Square	1,228	13.8	0
Westminster 015B	Lancaster Gate	1,206	13.6	0
Westminster 014F	Westbourne Park	1,097	12.3	1
Westminster 009A	Marylebone	905	10.2	0
Tower Hamlets 033A	Canary Wharf	904	10.2	12

4.6.1.2 Understanding charging behaviour: off-shift

Off-shift charging was analysed for the first time from June to October 2020. Off-shift charging was far more dispersed across London as off-shift charging drivers were assumed to charge near their homes (Figure 39) While on-shift charging was characterised by an intense concentration of demand on Rapid and Ultrarapid CPs in Central London, off-shift charging was multi-faceted as drivers utilised a range of Slow, Fast and Rapid CPs, as well as a mixture of both public and off-street, private charging infrastructure.

The trials found that Barnet was the LSOA supporting the most Uber EV off-shift charging demand, and it has remained the top borough throughout the research (Table 28). In the period between February to April 2021, Barnet experienced 8,314 charge events with more than 3,000 of them being at slow or fast public CPs. Fewer than 400 charge events were from a Rapid CP. It was found that the peak in off-shift charging occurred at 8pm and this would remain largely consistent across the entire data collection period.

Figure 39 – A CP distribution map across London boroughs for off-shift charge events, based on data taken from June to October 2020

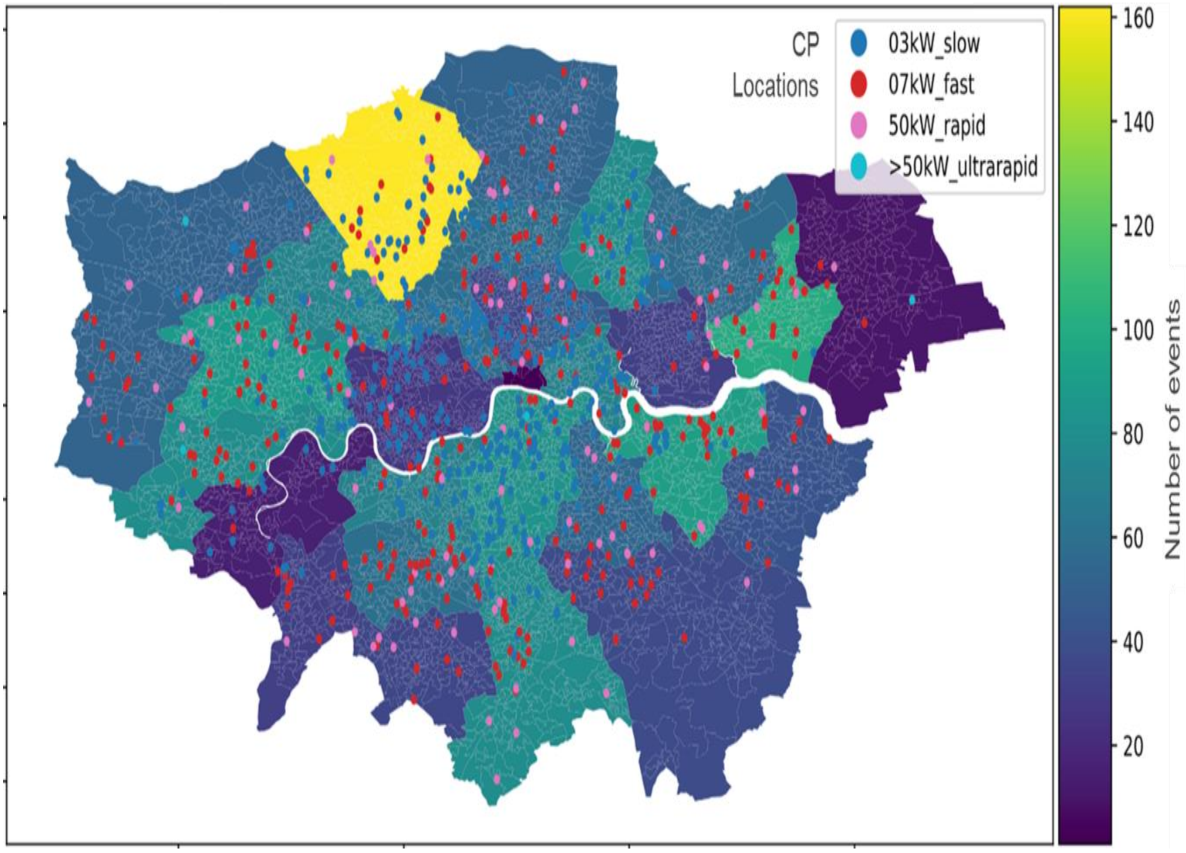


Table 28 – Top 3 London boroughs for Uber EV off-shift charging, based on data from June to October 2020

Ranking of borough by number of off-shift charge events	Home borough (regardless where charging happens)	Sum of all off-shift charging events by vehicles based in borough	Public charging events by CP type			Home charging events in borough	Borough average off-street parking access (%)
			Slow	Fast	Rapid		
1	Barnet	8,314	30%	7%	5%	59%	59%
2	Croydon	5,512	28%	12%	11%	49%	55%
3	Ealing	5,284	19%	11%	6%	64%	56%

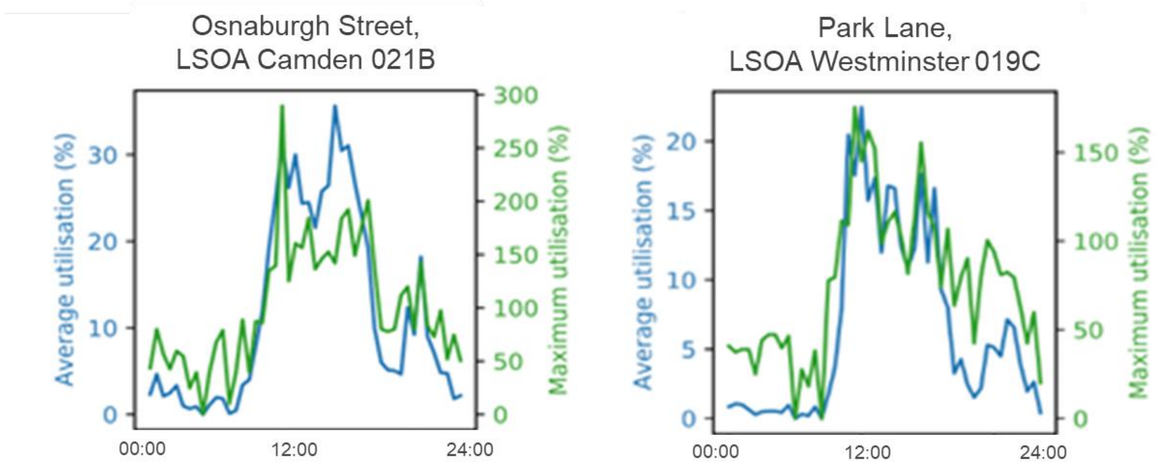
Overall, off-shift charging drivers without home charging access were primarily estimated to be using slow, public CPs. The trials observed most vehicles' SoC were greater than 50% when they concluded their shift and started their trip to a CP. This, coupled with the fact off-shift charging drivers could benefit from a longer charging window, makes it far more feasible to use Slow and Fast chargers. Consequently, proximity to a CP was far less of a concern for those charging off-shift, and they could capitalise on far more options for where to charge.

4.6.1.3 Excess demand at London CPs

A key finding of analysis on charging behaviour was there are not enough Rapid or Ultrarapid CPs in London to support the demand of Uber drivers charging on-shift. They may have to travel far to reach the optimally located CP and the modelling predicts that a number of the most popular CPs have a demand in excess of supply at peak times. An expected result of this is drivers would be forced to queue in order to charge, or not use the optimum CP.

This demand and supply imbalance was most intense in Central London, particularly in Westminster and City of London. The maximum and average utilisation rates for Osnaburgh Street and Park Lane exemplify this (Figure 40). Osnaburgh Street, situated in Camden, was the CP with the highest demand throughout the entire year and peak demand reached almost 300% of its capacity. Demand at the Westminster Park Lane site exceeded 150% of maximum capacity.

Figure 40 – Maximum and average demand/utilisation rates at two of the most popular CPs in London for Uber EV drivers, based on data from February to April 2021

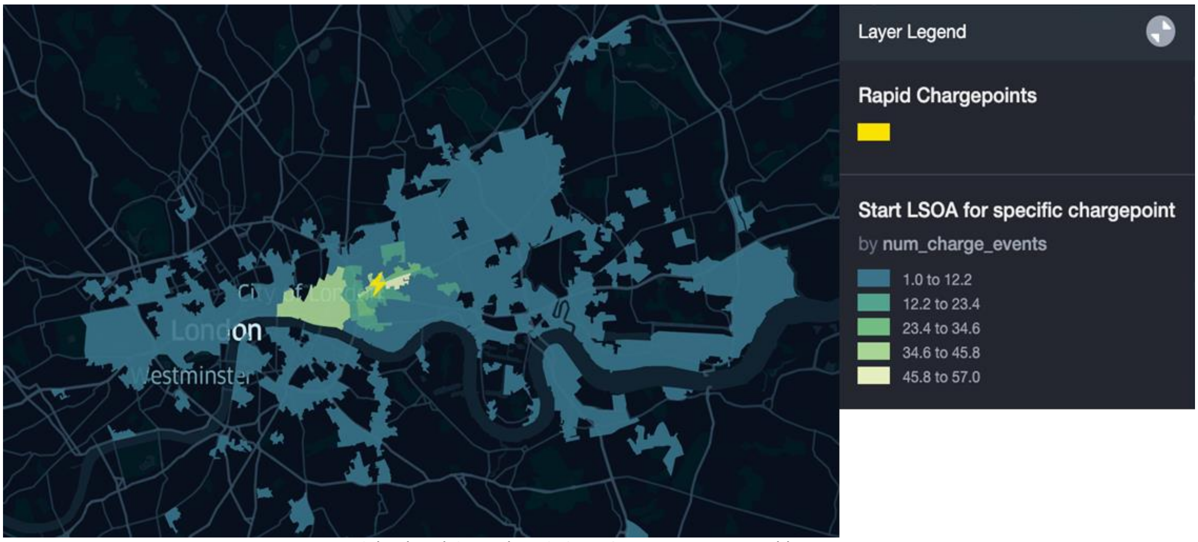


It was evident that high charging demand was occurring in areas that contained relatively few Rapid and Ultra-rapid CPs. The trials consistently proposed City of London and City of Westminster to be the most suitable areas to upgrade the existing charging infrastructure. Throughout the research period, Westminster did benefit from a number of new CP installations that soaked up a lot of charging demand. Chargers at Westminster Park Lane, Lancaster Gate, Westbourne Park and Marylebone have been installed as the trials have progressed and now represent nearly half of the top 10 most-utilised CPs in the city (Table 27).

The Park Lane location (which is operated by BP Pulse, with specific chargers reserved for Uber drivers) became available to Uber drivers from October 2020, and accommodated 926 charge events between November 2020 and January 2021. The other three additions, all public chargers, were installed and available from December 2020 or January 2021. There were 3,208 charge events in the LSOAs in which they were located from February to April 2021, indicating they were well-placed to cater for on-shift Uber EV charging demand. Having advocated for greater investment in Westminster, the significant success of these Westminster based Rapid/Ultrarapid CPs validated the analysis being conducted by the Optimise Prime team. As a result of these new CPs, the modelled over-utilisation at some existing CPs has reduced, though this has been tempered by the overall growth in EV charging demand.

Another result of the lack of sufficient charging infrastructure in Central London was that drivers were travelling significant distances – more than 4 km – to secure a charge. This was the case across the city, but the centrally located Rapid and Ultrarapid CPs were especially absorbing demand from distant areas across expansive catchment areas. The Shell Recharge location in Whitechapel, which was consistently amongst the Top 10 most-utilised CPs throughout the year, supported a vast catchment area. Positioned further to the East of London, its catchment area sprawled across to the boundaries of the city in the East while still accommodating significant charging demand from the centre (Figure 41).

Figure 41 – Catchment area for the CP at Shell Recharge in Whitechapel, February-April 2021



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The catchment area for Osnaburgh Street CP was another good example of this (Figure 42) It was capturing both concentrated demand from inner London boroughs, as well as disparate demand from outer regions of the city.

Figure 42 – Catchment area map for the CP at Osnaburgh Street, February-April 2021

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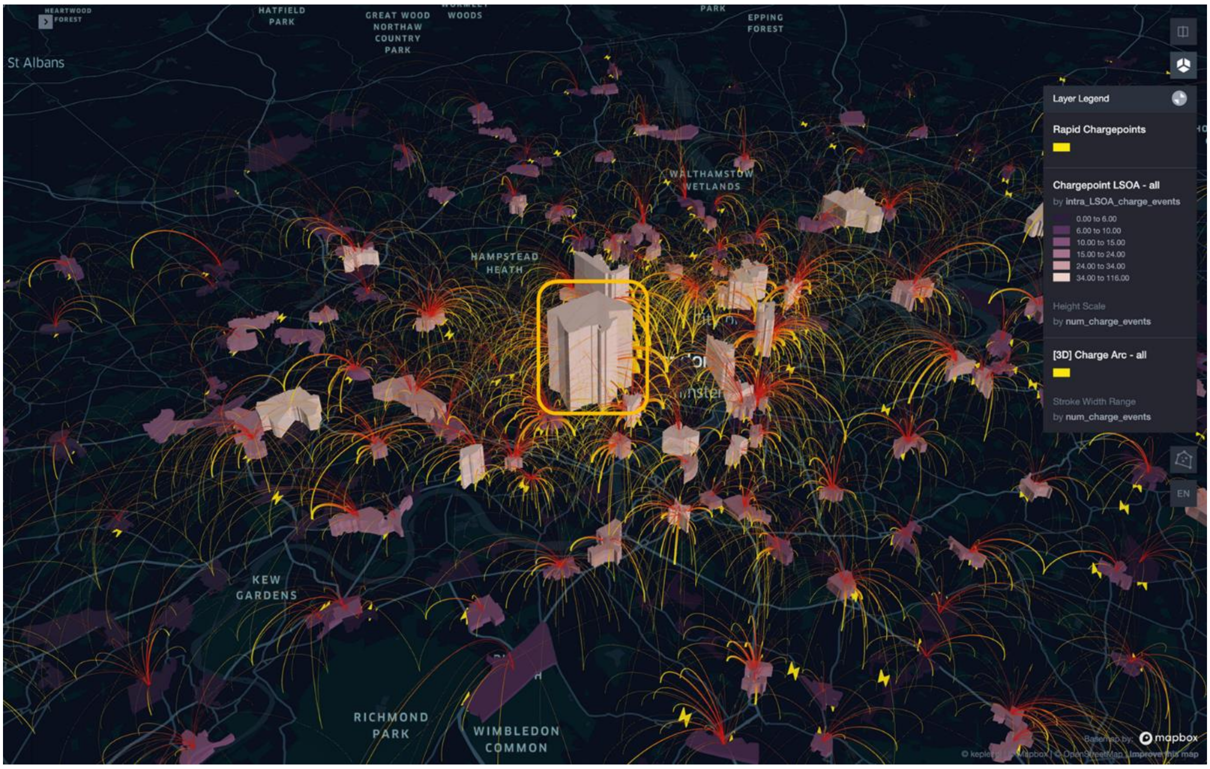
The Westminster Park Lane location was also accommodating sporadic demand from a significant distance away, as shown in Figure 43. Though centrally located, the average distance travelled to reach the Park Lane site was 4.7km. LSOAs within Westminster borough made up six of the 10 LSOAs where drivers most frequently had to travel out of in order to charge (according to data taken from February to April 2021).

Figure 43 – Chart visualising Uber EV driver movement towards CPs from the location in which it was inferred they would need to go to charge. The yellow box labels the Westminster Park Lane CP.



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In the arc, thickness is proportional to the number of trips, for which yellow indicates the source and red the destination. The height for each block represents the total number of charge events in that CP LSOA.

The trials established a connection between the LSOAs where drivers most frequently had to travel out from in order to reach a CP, and the LSOAs from which drivers had to drive the furthest in order to charge. Table 29, using data from before the COVID-19 lockdowns demonstrate this link by colour coding the LSOAs that were forcing drivers to both to travel the furthest (in the left table), and most often (in the right table) beyond their limits, to secure a recharge. A more recent analysis from 2021 can be found in Appendix 6.10, showing that a similar pattern continues to exist, albeit with a reduction in frequency of events on the Heathrow Airport corridor and a greater proportion of events in and around central London.

Table 29 - The LSOAs which drivers had to travel the furthest from in order to reach a CP (left table) and where drivers most frequently had to travel to other LSOAs in order to reach a CP (right table) (November 2019 to February 2020)

Starting LSOA	LSOA Description	Total no. of charge events from LSOA*	Average distance to CP (km)
Hillingdon 031A	Heathrow Airport	324	10.46
Hounslow 010D	Hounslow N Henlys Rbout	71	8.64
Hillingdon 031C	Harlington Sipson Road	45	6.48
Newham 013G	Stratford Stn & Westfield	55	6.01
Hammersmith & Fulham 004A	Shep. Bush Westfield	70	5.95
Westminster 011B	Portman Sq/ M'bone Ln	64	5.45
Westminster 008D	Regents' Park West	31	5.42
Westminster 015G	Paddington Praed St	55	5.36
Westminster 018A	Leicester Square	49	5.32
City of London 001F	City	137	5.30

Starting LSOA	LSOA Description	Total no. of charge events from LSOA*	Average distance to CP (km)
Hillingdon 031A	Heathrow Airport	324	10.46
Hammersmith & Fulham 013E	Hammersmith S. of flyover	151	4.61
City of London 001F	City	137	5.30
Westminster 018D	Central/South Mayfair	103	5.23
Hackney 027G	Shoreditch	99	4.34
Westminster 018C	St James & Whitehall	89	4.41
Westminster 013E	Regent Street	79	4.37
Hounslow 010D	Hounslow N Henlys Rbout	71	8.64
Hammersmith & Fulham 004A	Shep. Bush Westfield	70	5.95
Westminster 013B	East Soho & Fitzrovia	68	4.80

Data on all of the LSOAs where drivers were having to travel over 4 km to recharge their vehicle has been mapped (Figure 44). Imitating the London skyline, the high LSOA blocks in Central London show the high propensity for long journeys to CPs there, with the large LSOA to the west depicting Uber EV drivers travelling long distances from Heathrow. Visualising this gave clear insight into the areas where investment could mitigate these long and inefficient journeys that Uber EV drivers were commonly having to make.

Figure 44 – The LSOAs where Uber EV drivers are driving more than 4km to reach a CP, with height of the LSOA block representing the volume of drivers being affected. Data taken from February to April 2021

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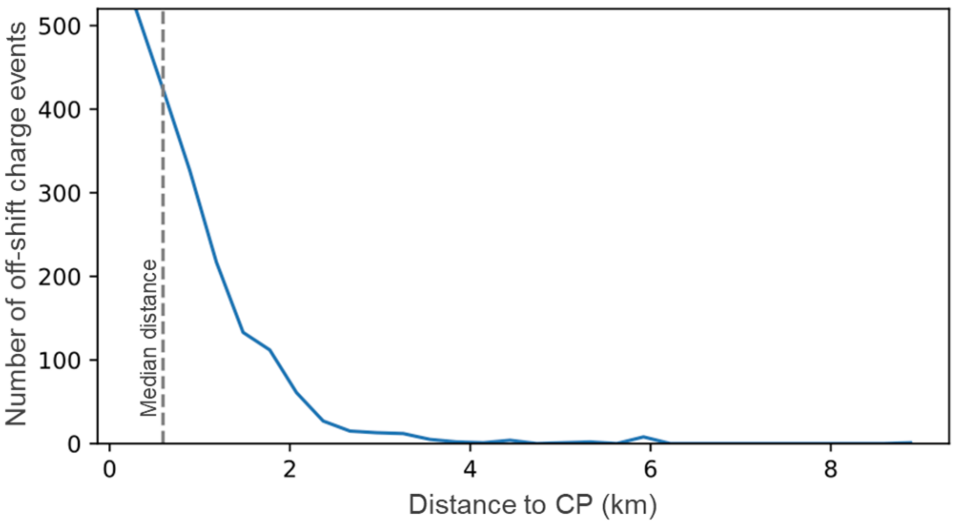
For the drivers using public CPs, there were more options available than for on-shift charging drivers. The longer window available until their next trip meant that they were not reliant on using rarer Rapid and Ultrarapid CPs in order to quickly boost their SoC. Within this longer timeframe, they could comfortably recharge before beginning their next shift, and so they could choose the most convenient location even if it was a Slow or Fast charger. These two effects resulted in the number of vehicles travelling significant distances to reach a CP being relatively low. Figure 45 shows distances travelled; the median distance travelled for off-shift charging was 0.6 km.

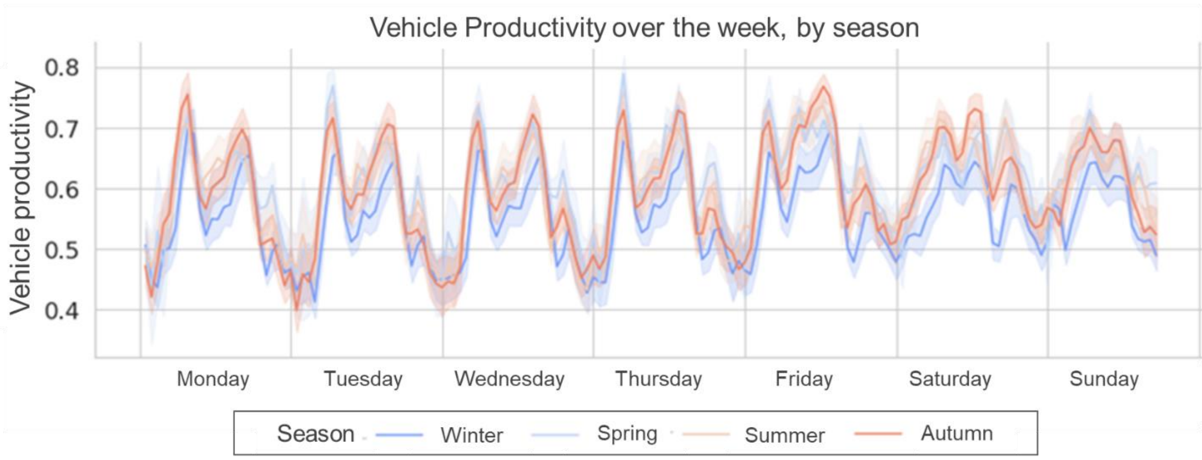
Figure 45 – Distances driven by Uber EV drivers to secure an off-shift charge, based on data taken from February to April 2021



4.6.1.4 Impact of weather and time

Sensitivity analysis was carried out in order to observe the impact of various weather conditions and time/seasonality on the modelled charging load from Uber EVs. Charging events appear to be consistent irrespective of weather conditions. The trials observed that productivity (a measure of how busy each vehicle was during a shift) remained relatively consistent across the year, with a clear pattern across days and weeks, as shown in Figure 46. Some seasonal variability can be seen, however this is relatively minor.

Figure 46 – Vehicle productivity compared against time of the year

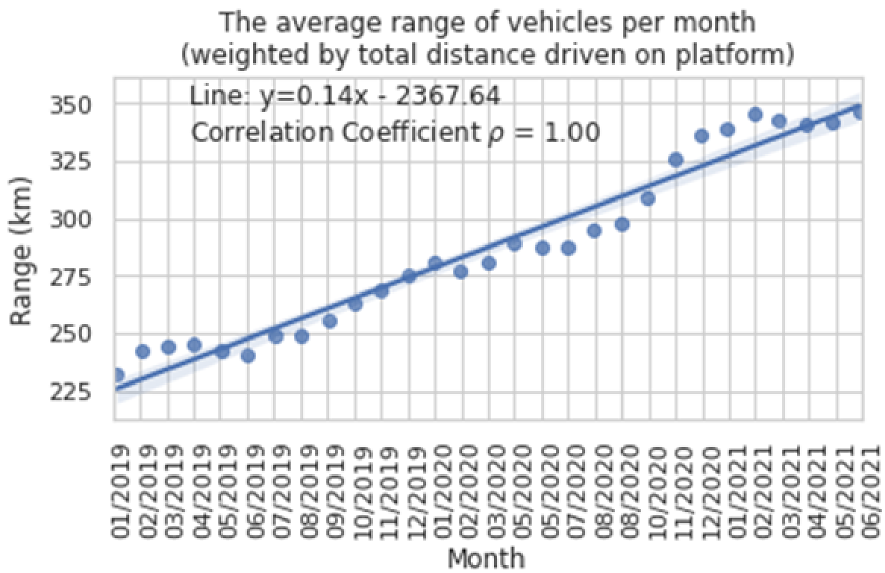


4.6.1.5 London CP proliferation and vehicle range growth

Tracking utilisation rates across the CPs in London, an uptake-delay was observed between installation and operation of a new CP, compared to when drivers started to use it. Three new CPs were installed in Westminster between December 2020 and January 2021, situated on Brook Street, Westbourne Park Road and Rossmore Road. These locations then supported 3,208 charge events from February to April 2021 and were placed in the Top 10 most-used CPs by June, but the uptake by Uber drivers was moderately slow shown by a month delay. It was suggested this could be owning to slow proliferation of knowledge of the new CPs, or inelastic driver behaviour.

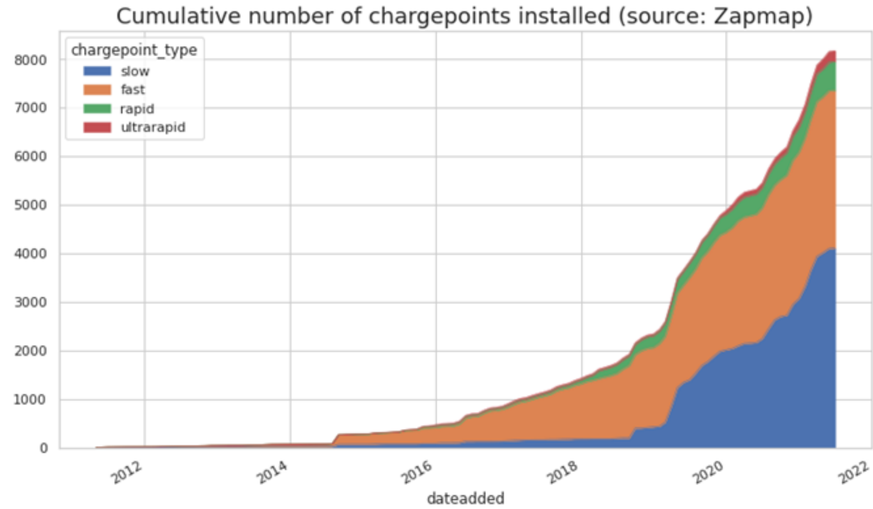
Over the course of the research period, the average vehicle range for Uber EVs grew from just over 225 km in January 2019 to nearly 350 km in June 2021 (Figure 47). This is most likely due to new vehicles becoming available to Uber drivers, and it is likely to continue. This may have an influence on charging behaviour and on the distribution network, since longer range vehicles may need to charge less frequently, but when they do, they will require more power in order to reach a full SoC.

Figure 47 – Uber EV vehicle range growth throughout the research period to date



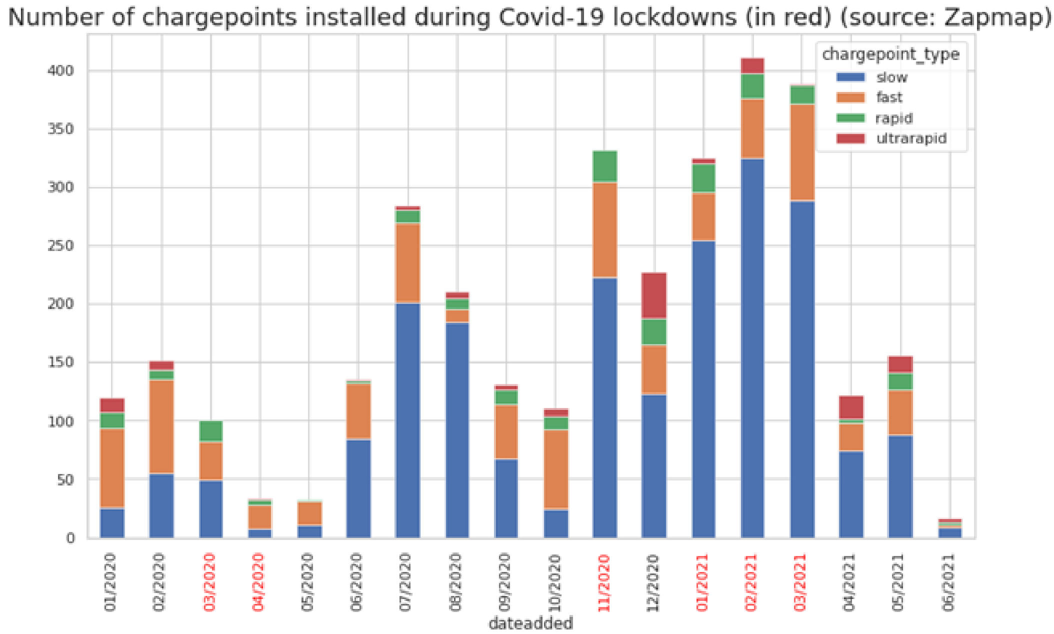
The charging infrastructure available for use in London has grown significantly too, and it appears to be accelerating. As shown in Figure 48, there are now 132% more Rapid chargers now compared with in January 2019, 177% more Rapid and Ultra-rapid chargers, and 229% more across all four charger types.

Figure 48 – Growth of number of CPs installed in London



Yet, while overall the charging infrastructure in London is growing, installations of Slow and Fast charging stations continue to dominate this growth. Rapid CPs appear to be installed in consistent but low numbers, whereas Ultra-rapid CPs are both installed intermittently and in relatively low numbers, except for in December 2020 which saw a considerable number of new CPs fitted (Figure 49). The slow chargers are predominantly those installed in lampposts in residential areas.

Figure 49 – CP installations in London. Dates coloured red indicate it coinciding with a COVID-19 related lockdown in the UK



4.6.2 Phase 2

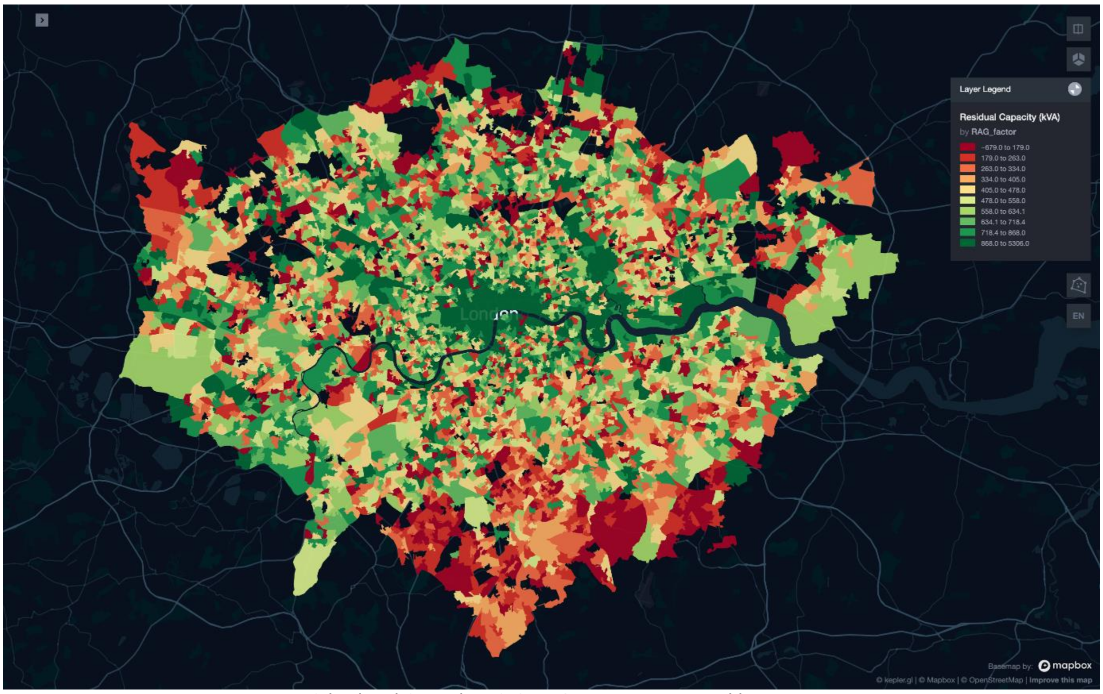
4.6.2.1 Impact of Uber EV charging on the grid

In parallel to the evaluation of Uber EV drivers' charging behaviour, the trials analysed the impact this charging demand was having on the grid. The key learning of this was there appeared to be sufficient network capacity to support additional charging infrastructure to meet Uber EV demand in Central London. The trials regularly produced Red-Amber-Green (RAG) maps which illustrated LSOAs across London and their respective headroom.

To construct these visualisations, residual capacity was calculated for each LSOA by taking the maximum historical demand at the substation which had the highest headroom. Then, by applying the estimated power demand from inferred charge events, a 'worst case scenario' for residual capacity could be found and mapped-out for each LSOAs most-constrained substation. This yielded two polarised outputs: the 10 substations with the least residual capacity could be found and tracked over the research period, while also it allowed estimation of the well-placed locations where new charging infrastructure for Uber EVs could benefit from ample headroom.

As Figure 50 depicts, areas in central London in particular may benefit from high degrees of spare capacity, as shown by the deep and largely uninterrupted green at the core of the map. This headroom could be utilised to support new CP installations to deliver Rapid and Ultrarapid charges to on-shift charging Uber EV drivers, who were identified as charging in that area predominantly.

Figure 50 – RAG map illustrating headroom capacity across London LSOAs, based on data taken from February to April 2021.



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The scale shows the available capacity of the substation with the most headroom in the LSOA less the total charge (kVA) of the highest number of charge events in a 30-minute window. The red areas show the areas with the least (or negative) available capacity.

In contrast, though the regions of network constraint – signified by the red colouring – were spread intermittently across the city, they are prominent in the outer boroughs. Network reinforcement may be needed in order to enable new CP installations in these locations. Importantly, these outer boroughs are where off-shift charging Uber drivers – who make up the majority of Uber EV drivers – go to charge at the end of their shift. Boroughs like Croydon, Barnet, Enfield, Lambeth, are all amongst the most common 'home' locations for Uber EV drivers (
Table 30) and all contain some of the most constrained substations in the city (Table 31).

Table 30 – Most common boroughs for off-shift charging, as of June 2021, with breakdown of predicted CP type used

Ranking of borough by number of off-shift charge events	Home borough (regardless where charging happens)	Public charging events by CP type, as % of all events			Home charging events as % of all events
		Slow	Fast	Rapid	
1	Barnet	30%	7%	5%	59%
2	Croydon	28%	12%	11%	49%
3	Ealing	19%	11%	6%	64%
4	Brent	37%	16%	3%	44%
5	Lambeth	69%	1%	5%	26%
6	Hounslow	43%	7%	1%	50%
7	Enfield	27%	13%	8%	53%
8	Southwark	81%	3%	5%	12%
9	Newham	43%	23%	7%	27%
10	Wandsworth	73%	3%	2%	22%
11	Merton	22%	16%	3%	59%
12	Greenwich	50%	7%	2%	40%
13	Tower Hamlets	90%	4%	0%	6%

Table 31 – LSOAs where substations have the least available capacity for charging, as of June 2021

CP LSOA	Predicted peak load from current Uber EV charging (kVA)	Times of predicted peak demand	
Croydon 004A	114	15:30:00	Friday
Enfield 033B	170	17:00:00	Tuesday
Greenwich 019D	106	17:30:00	Tuesday
Enfield 020A	100	15:00:00 12:00:00	Thursday Friday
Hackney 029B	100	10:30:00 14:30:00 18:30:00 20:00:00 13:30:00 11:00:00	Monday Monday Tuesday Wednesday Friday Saturday
Barnet 023A	53	18:00:00 18:30:00	Friday Friday
Camden 015C	53	17:30:00	Thursday
Haringey 029C	53	12:00:00	Sunday
Lambeth 007E	50	16:30:00	Thursday
Richmond upon Thames 006B	50	14:00:00 14:30:00	Friday Friday

The trials consolidated this data and identified the number of additional CPs that could be immediately accommodated by substations in the three LSOAs which were most deprived of sufficient charging infrastructure (Table 32). Hillingdon, which serves demand from drivers completing trips to and from Heathrow Airport, could support 12 new Rapid CPs. Westminster could also support an additional 12 Rapid CPs, whereas City of London, the other area continuously identified as lacking in sufficient charging infrastructure, could accommodate up to 41 new Rapid CPs. Barnet and Croydon, the boroughs hosting the most ‘home’ Uber EV drivers, could each accommodate 2-14 Rapid CPs. In all cases, there was sufficient electrical supply capacity to provide enough CPs to satisfy current Uber EV demand in the region. Appendix 6.8 maps out the distribution of substation headroom for each LSOA recommended by the trials.

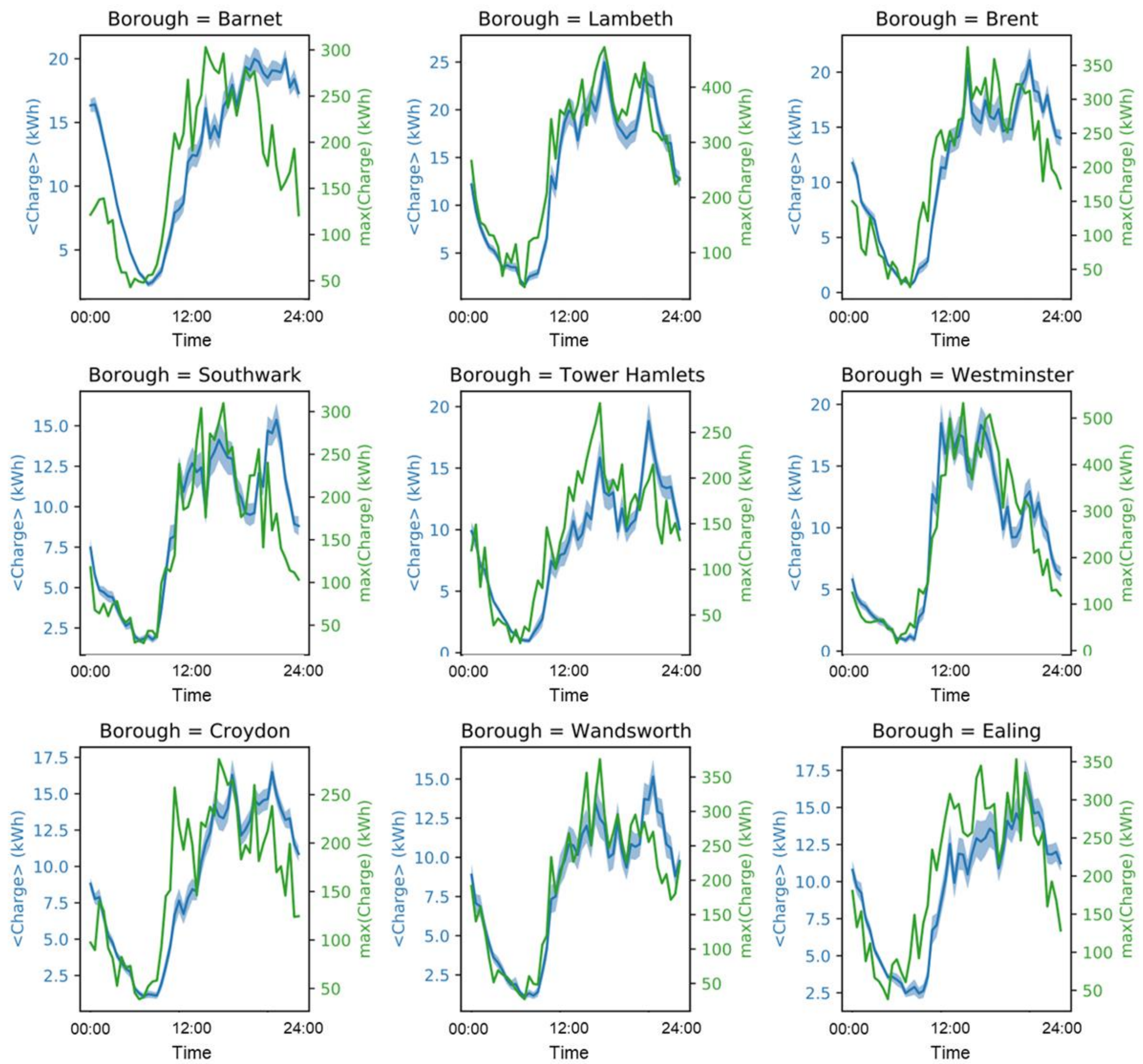
Table 32 – List of the LSOAs most lacking in CPs, the number of CPs that could be immediately connected to existing substations (not taking into account physical space constraints), and the number required to satisfy current Uber EV demand

Chargepoint LSOA	Chargepoint LSOA Description	Number of *available* substations in LSOA	Headroom of max capacity *available* substation (median shown in brackets) (kVA)	Maximum current Uber charging power usage (kVA) in half hour period	50kW chargers that could be connected to substations in LSOA [Max (*median*)]	Estimated new chargers required to meet current Uber demand
City of London 001F	City of London	268	2,089 (574)	7	41 *(11)*	3-6
Hillingdon 031A	Heathrow Airport	7	630 (228)	7	12 *(4)*	1-3
Westminster 011A	Mayfair	19	637 (251)	0	12 *(5)*	3-6
Barnet 012D	Woodside Park	6	724 (320)	0	14 *(6)*	1-2
Bexley 016B	Welling	5	727 (256)	200	10 *(1)*	1-2
Croydon 007E	Norwood Junction	2	118 (71)	0	2 *(1)*	1-2

4.6.2.2 Peak in demand

Averaged over all boroughs, the peak in electricity demand for Uber EV charging arrives at 8pm, with a minor secondary peak existing in the early afternoon. Figure 51 shows the demand peaks per borough for the boroughs with the most charging events. This peak profile been observed to stay relatively constant throughout the year, although from June to August 2020 this peak was shifted slightly earlier in the day, most likely owning to post-coronavirus conditions (reduced prominence of rush hours, reduction in office days and a stifling of nightlife could have contributed to this change).

Figure 51 – Maximum and average charge demand over the day for the boroughs with the most charging events (combination of on and off shift, February-April 2021)



4.7 *Insights gained*

The WS3 trials conducted using data from Uber trips throughout Greater London are now at an advanced stage and are delivering learnings that will help the project meet the trials' objectives.

4.7.1 Addressing the experiment hypotheses

Ub_Ex_01 Initial hypothesis: The time, location and magnitude of electric PHV charge events can be estimated from Uber trip data

The trials have successfully developed a model of the charge events that would occur based on Uber data. A range of techniques have been used to identify when charge events could occur, and, based on several factors when drivers charged during the day. Where charging during the shift was found to be unlikely, the charging was ascribed to an estimated home location.

The magnitude of actual charge events was then modelled, based on drivers using the most optimal public CP for their journey. For both on-shift and off-shift charging the load on the network is likely to peak in the evening, as vehicle batteries become depleted and daytime drivers return home.

Ub_Ex_02 Initial hypothesis: The time, location and magnitude of electric PHV charge events will be influenced by external factors such as weather and large public events

Weather and time have so far been studied as potential influencers on charging patterns.

It was found that weather has very little impact on EV trip volumes, and hence on the level of charging that is being modelled. It is possible however that weather affects the efficiency of vehicles – this impact cannot be estimated from the Uber trip data alone, and the telematics data from WS1 and WS2 will help in quantifying this effect.

Time was found to have a greater influence than weather on trip and charging patterns. There are definite patterns in daily and day-to-day trip demand, and this has a knock-on effect on when drivers need to, and are able to, charge.

Ub_Ex_04 Initial hypothesis: Locations lacking adequate charging infrastructure (current and future) can be inferred from Uber trip data

The trials have mapped both where drivers actually charged (as in Ub_Ex_01) and where drivers were when they decided they needed to charge. Based on this the project was able to develop a range of indicators of the adequacy of charging infrastructure. There are several locations where drivers have to travel a significant distance in order to charge.

LSOAs were ranked on the frequency and distance that drivers had to travel from them in order to charge. Central London areas in the City of London and City of Westminster ranked highly in both of these counts due to the low number of rapid CPs and the high volume of journeys undertaken. For off-shift charging, where long charge events will not impact on abilities of drivers to earn, drivers can more easily utilise the larger number of slow and fast CPs.

Individual CPs were also studied and, based on the optimal CP modelling, the most popular CPs in London are utilised way beyond their capacity, suggesting drivers will have to queue in order to charge when they are at their busiest, or travel further in order to use non-optimal CPs. Again, CPs in and around the City of London and City of Westminster were identified as the locations with the highest modelled utilisation, so adding to the charging infrastructure there is recommended. CPs that were added in these areas, particularly in Westminster, during the project were very successful in accommodating Uber EV demand.

The project team have now started work on modelling future demand growth, and the impacts this will have on infrastructure provision.

Ub_Ex_05 Initial hypothesis: electric PHV charging causes low magnitude, local stress on the distribution network at present, but will pose a more significant threat in the next 10 years

Initial work on distribution network impact has involved overlaying the current charging demand in each LSOA on substation capacity, in order to develop heatmaps of areas where constraints may be encountered in the future. This initial analysis has shown that there is significant variation across the city, although Central London, where on-shift charging takes place is likely in a better position to accept additional demand than the suburban areas of the city where drivers live.

Investigation will continue, utilising the models of future growth from Ub_Ex_04 and using the data collected in the trial as an input to UK Power Networks' strategic forecasting tools to deliver a greater insight into network impacts.

4.7.2 Other learnings

In addition to the learnings that directly address the trial hypotheses Optimise Prime has generated a number of learnings from the analysis of the WS3 data:

- **Availability of EVs and CPs continues to evolve:** Throughout the period of the trials consistent growth has been seen in both the range of vehicles in the mixed trials and the availability of charging infrastructure. Both of these are likely to have a material impact on the trials and charging requirements, if this continues, and need to be factored into future growth and charging behaviour models.
- **Vehicle type appears to influence journey type**: The vehicle type an Uber EV driver uses can influence the type of trips they conduct. EVs with low range were less likely to complete trips to airports, and high range vehicles were less likely to operate at weekends.

4.8 Next steps

WS3 is the most advanced of the three trial workstreams, having been subject to less of a delay in vehicle availability, as such to models for analysing the data in this workstream are well developed. Next steps in WS3 will involve continuing the analysis carried out to date and extending it with a particular focus on:

- Forecasting the impact of future EV growth, based on projections of PHV electrification and analysing how Optimise Prime's data on EVs can improve existing EV uptake models
- Analysing the impact of future electric PHV demand on the distribution network, in terms of capacity and cost
- Considering the potential for flexibility provision if the Optimise Prime flexibility and Profiled connection products can be applied to electric PHV charging.

In Deliverable D5, the project will report on behavioural studies conducted with Uber drivers to gauge attitude to EV adoption.

4.9 Changes made or planned from initial trial design

The WS3 trials have generally proceeded to plan and it is not anticipated that changes will be made to the trial methodology.

5 Conclusions and Next Steps

5.1 Conclusions

This report forms the fourth Optimise Prime deliverable. The project has significantly progressed and this report provides a comprehensive summary of the activities that have taken place in the early stages of the trials and the learnings gained from this work. The experiments are continuing and the final results will be featured in future deliverables.

This report should prove valuable to any DNO considering how to plan for the future growth of commercial EVs. The trial methodology may also prove useful to DNOs planning to implement similar innovation projects in the future. Vehicle fleet operators planning their transition to EVs should also find elements of this deliverable valuable, especially the lessons learnt regarding use of EVs. Charge Point Operators may find the projects findings around demand for charging useful to their businesses, and government organisations may find the findings useful as they plan for future EV infrastructure.

Through the initial analysis of the available data, the Optimise Prime team has built several models in order to forecast future EV power demand from ICEV activity and has begun analysing EV data from the fleets in order to validate these models. Through the analysis of the Uber journeys, initial conclusions have been reached around the adequacy of current charging infrastructure and work has looked at comparing gaps in provision to network capacity. Future work will focus on modelling future growth of electric PHVs and the resulting requirements on charging infrastructure and the distribution network.

As mentioned in previous deliverables, the design of the Optimise Prime trials build on learnings from several other Ofgem funded innovation projects and this deliverable report ensures future Innovation projects can build on the learning from Optimise Prime.

Data capture, analysis and trialling activities will continue over the coming months in order to build on the insights presented in this report. Alongside the data science team, the project's business modelling workstream is considering behavioural and economic aspects of the EV transition for fleets – the next deliverable, D5 will capture the initial insights from the trial activities.

For further questions on the evidence provided in this report, or more general questions about the project, please contact Optimise Prime team at: communications@optimise-prime.com or visit the project website www.optimise-prime.com.

5.2 Next steps: Open items & future activities

Following on from the initial findings the Optimise Prime trials will continue until the end of June 2022. Throughout this period the project team will focus on:

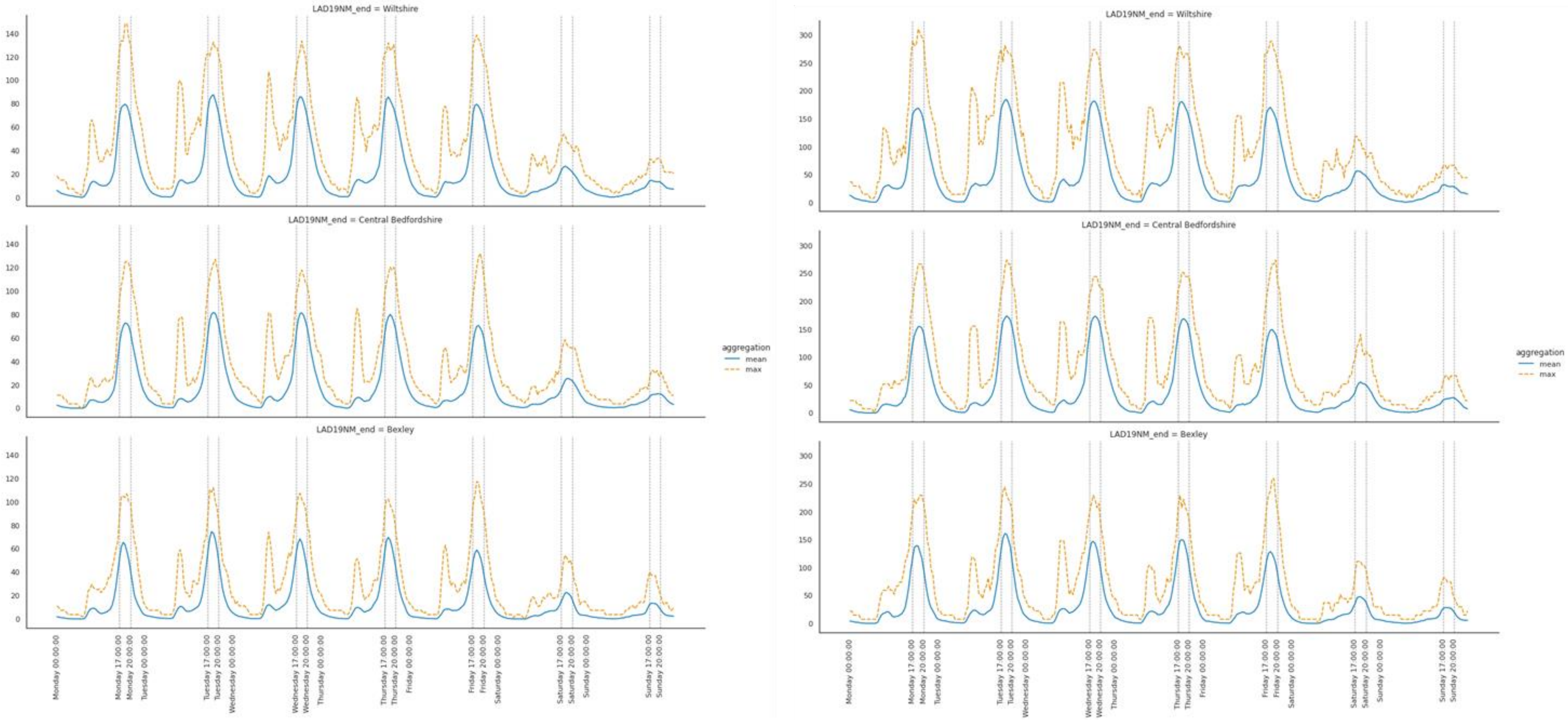
- Running executions of all of the Optimise Prime trial experiments, including looking in greater detail on the future impacts of EVs on distribution networks, based on what the project is learning about EV use
- Continuing to run a range of flexibility and profiled connection trials to prove the effectiveness of the project's methods
- Continuing to adapt the trials and experiments to increase value gained from the project based on the findings from the early trialling activity,
- Continuing to collect a comprehensive dataset on EV use and charging behaviour

- Conducting further behavioural studies related to EV adoption, and economic analysis of the impact of electrification on fleet TCO, the first results of which will published in the next deliverable, D5
- Utilising project data with UK Power Networks' Strategic Forecasting System in order to quantify network impacts of EV adoption and the project methods
- Continuing to engage with stakeholders through communications and events.

6 Appendices

6.1 Rich view of the potential energy and power demands initiated by British Gas home charging

Figure 52 – Potential energy and power demands of British Gas home charging at 3 selected LADs. Realpower [kW] on the left, Energy (kWh) on the right hand-side.



6.2 Smart charging programming logic

The logic for peak load minimisation is as follows:

- For each PTU, the headroom is determined by finding the difference between an initialised capacity constraint and the historical maximum background load for that PTU
- For each PTU, vehicles are ranked based on how urgent it is for them to charge (i.e. the further away they are from a full state of charge, and the closer they are in time to being required to complete operations, the more urgent it is for them to charge)
- Factors are then calculated to determine what portion of the headroom gets allocated to each vehicle for charging, and subsequently, the demand associated with charging each vehicle during each PTU is calculated
- Until simulated vehicles have demonstrated that they're managing to keep above a minimum state of charge that has been specified (e.g. 20%) throughout the week, the simulation is infeasible and the capacity constraint is increased and reinitialised. The 20% figure has been chosen based on the assumption that drivers will not want to operate vehicles where the battery is close to empty.
- Once a feasible simulation has been completed, the associated capacity constraint value is the minimised peak load value (assuming no LCTs at the site)
- As for the unmanaged charging mode, vehicles are charged in batches, filling up according to the time they enter the depot, and batches thereafter prioritised according to the urgency rankings defined above. In the case where the number of CPs is less than the number of vehicles, this is an important consideration, especially since this base model assumes that when a batch has finished a new batch immediately starts at the next PTU. The business assumption in the simulation is that there is someone in the depot able to change over these vehicles at all times.

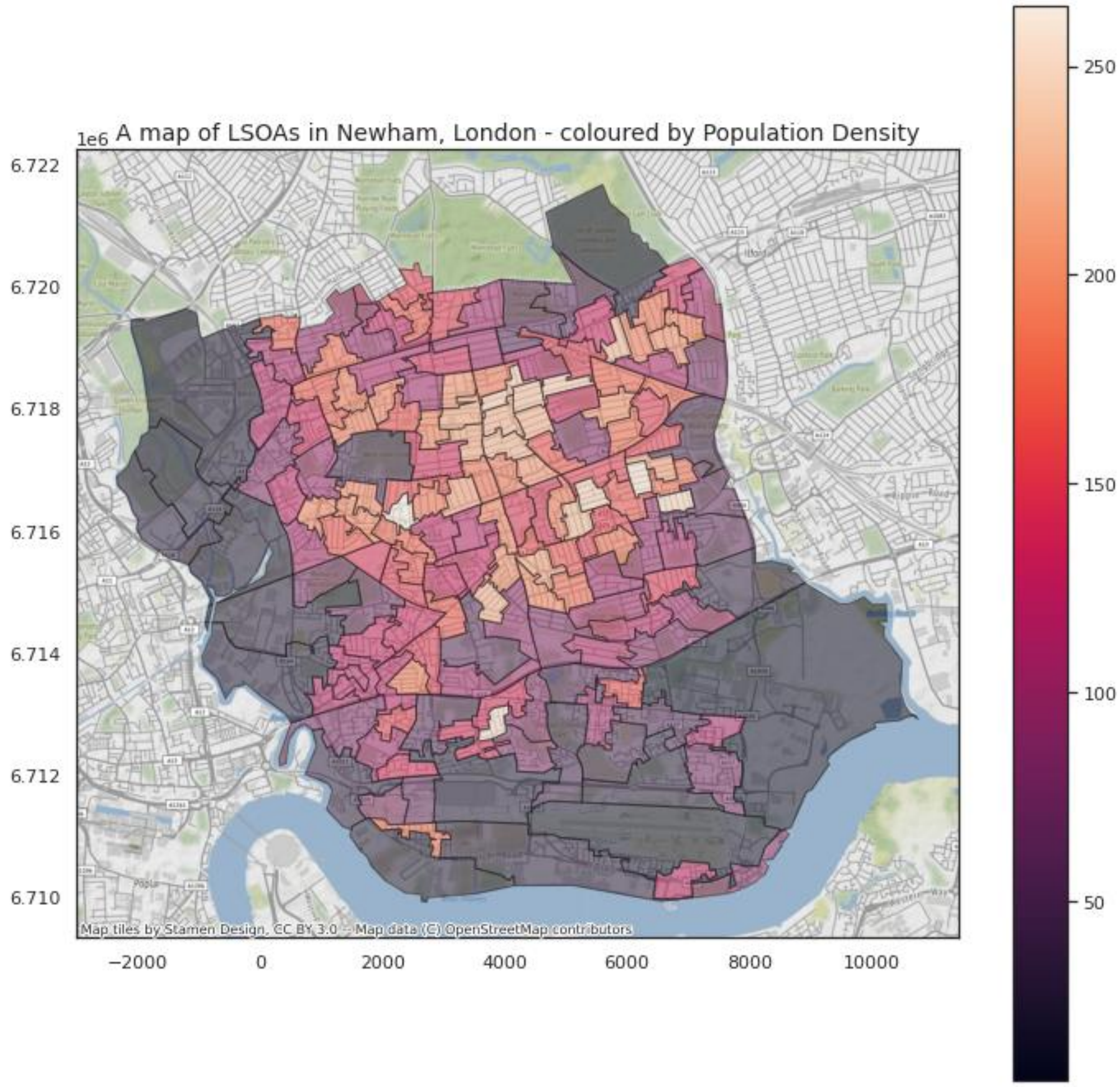
The logic for cost minimisation is as follows:

- Given that peak load minimisation has been simulated, the peak load value acts as a constraint in cost minimisation modelling
- Linear programming logic is used to determine a charge schedule, such that, the energy bill associated with charging is minimised
- For this to be valuable, the depot is modelled to have a time of use tariff

The linear program is subject to various constraints, such as total load not being able to exceed the previously calculated minimised peak load and the minimum SoC always exceeding a user-specified threshold.

6.3 Example of Newham borough and the LSOAs contained within it, coloured by population density

Figure 53 – LSOAs in the London Borough of Newham



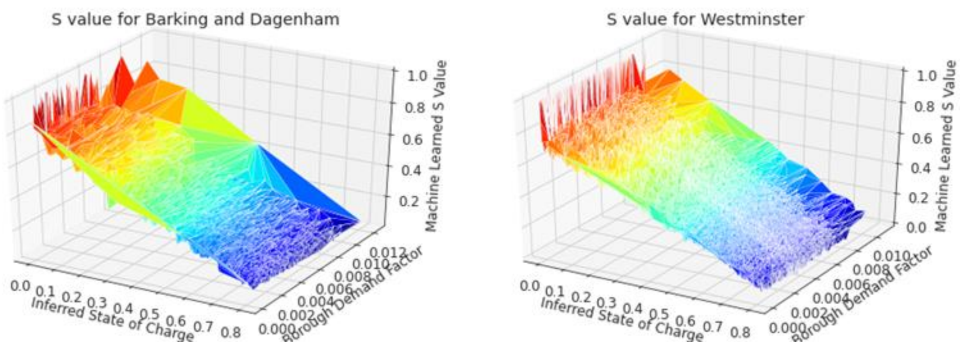
6.4 *Should Charge (S Value) Methodology*

Range Anxiety, based on an inferred SoC, was used to model whether drivers *should* charge. The model assumes vehicles start with at least 80% SoC, if following a trip their inferred SoC was low, the probability they *should* charge would be high; and if SoC was high, then the probability they *should* charge was low.

To calculate shift demand, the trials assumed Uber drivers would seek to maximise their time on shifts, and so would not charge when the demand from passengers for an Uber trip in the local area was relatively high, with demand being defined as historical "en-route" that occurred in that area. If the demand for the area they were operating in at that moment was relatively high (for their shift) then the probability they should charge was low, with the converse proving to be true.

The Trials would machine learn the weighting of these two functions. The resulting S values were borough independent:

Figure 54 – Examples of S-values



6.5 *Did Charge (D Value) Methodology*

Having confirmed that it was physically possible to charge using a CP in an available time on an open/offline event chain, the trials would then determine if the driver did go to charge based on the following properties: the inferred S value, and the SoC increase from the optimal CP.

A charge event could be confirmed if the D value (formed by evaluation of the previous two properties) was greater than 50%.

6.5.1 The inferred S (*should*) value

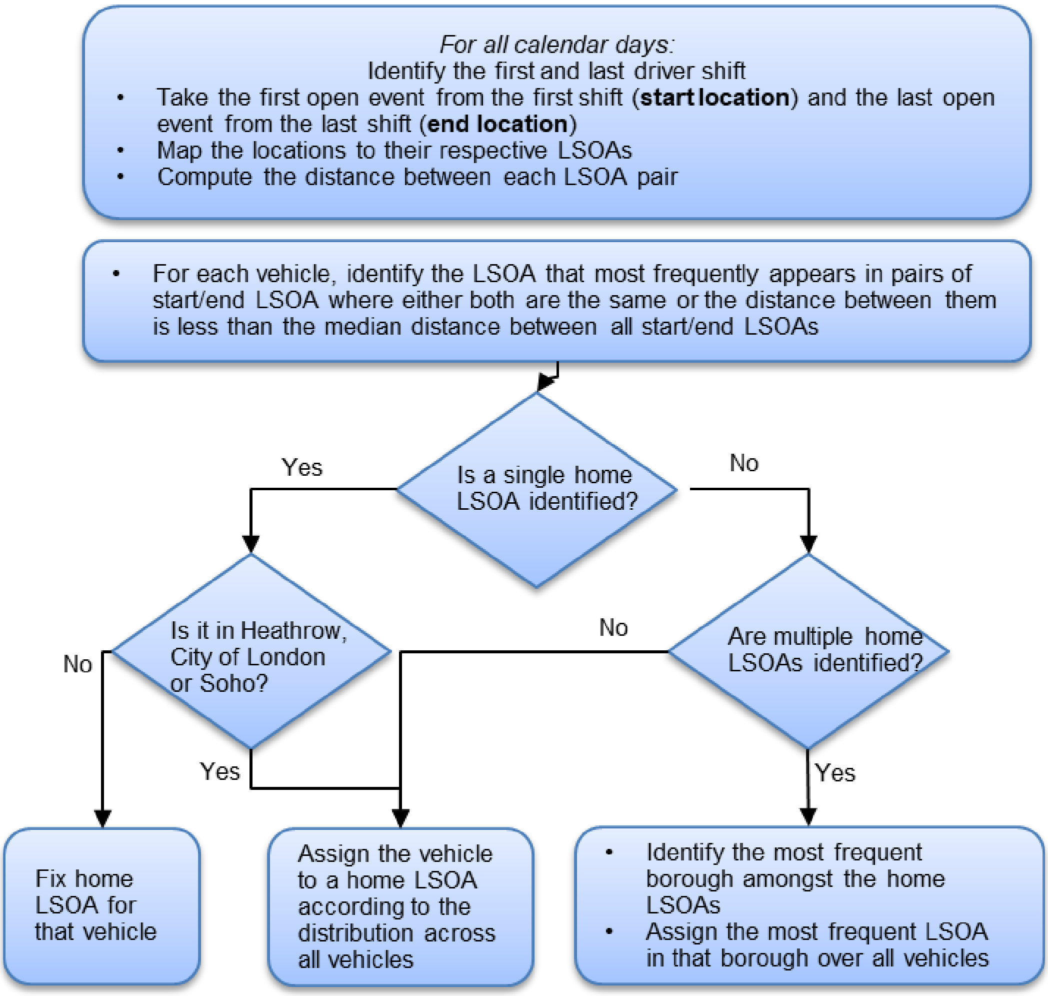
Given it was possible for a driver to charge, a probability that they did charge would then be decided according to the inferred *should* value. If this was higher, then it was deemed more likely they actually did go to charge. Essentially, the probability a driver did go to charge increased proportional to the fact that they should go to charge, given that they could have gone to charge.

6.5.2 SoC increase from optimal CP

A driver is more likely to go and charge if they would receive more charge from the optimal CP. However, this would only be true to a certain extent, since drivers also have to complete trips and so their sole focus is not boosting the charge of their vehicle. Consequently, the trials decreased the probability that they did charge if the SoC gained from a CP was "too high" (approaching a full/complete charge) to reflect this.

6.6 The logic for assigning each Uber driver a 'home' location

Figure 55 – Uber home location assignment logic



6.7 Off-street parking levels, TFL Data

(source: http://content.tfl.gov.uk/travel-in-london-report-12.pdf)

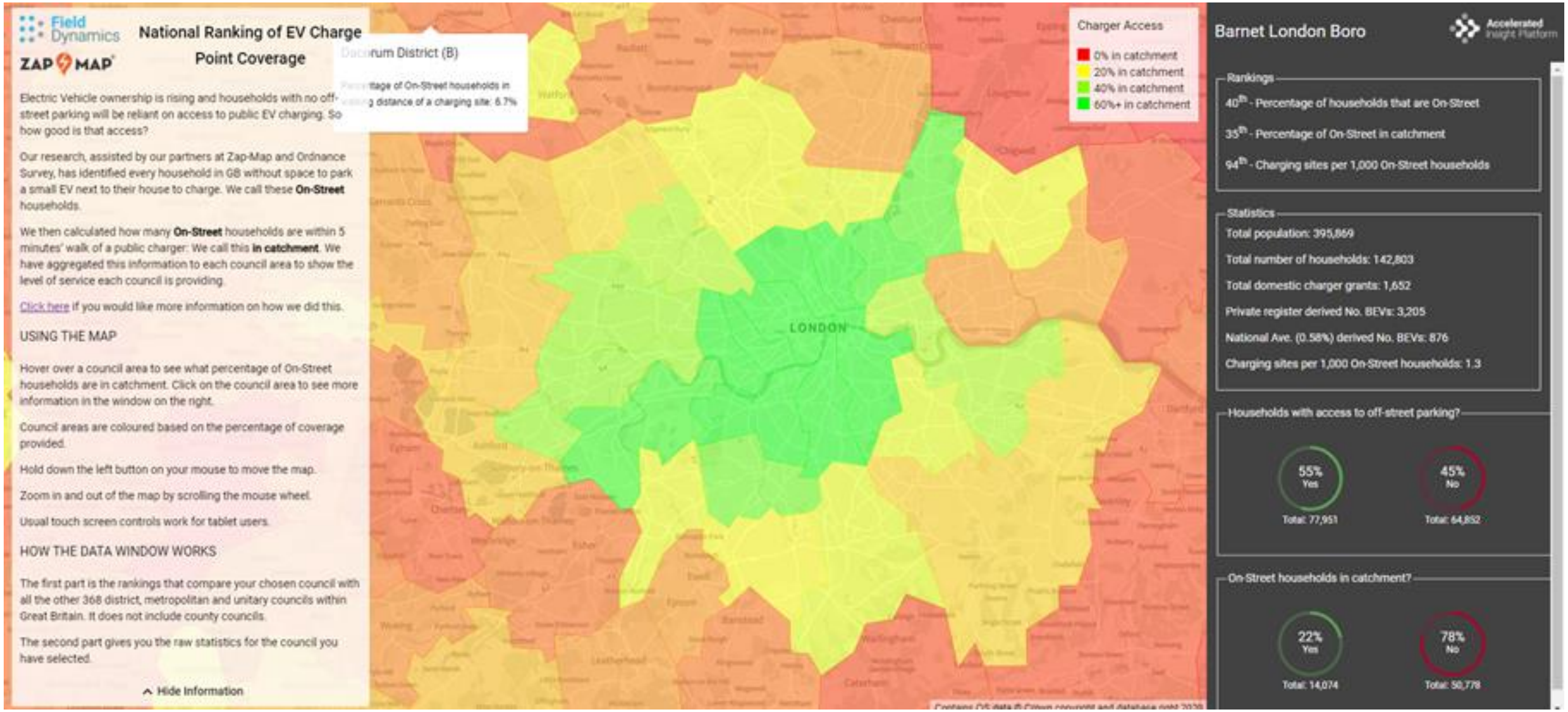
Table 33 – On/Off street parking numbers by London borough

Borough	Parked on-street	Parked off-street	Parked on-street	Parked off-street
Bromley	35,370	124,287	22%	78%
Croydon	52,405	101,137	34%	66%
Barnet	47,597	100,051	32%	68%
Hillingdon	34,388	103,291	25%	75%
Enfield	53,106	79,439	40%	60%
Havering	22,381	98,755	18%	82%
Ealing	58,247	60,447	49%	51%
Bexley	29,087	84,750	26%	74%
Redbridge	28,829	84,358	25%	75%
Hounslow	40,586	65,370	38%	62%
Harrow	26,333	75,599	26%	74%
Wandsworth	65,891	29,068	69%	31%
Sutton	20,666	73,177	22%	78%
Greenwich	43,365	48,500	47%	53%
Brent	37,216	54,155	41%	59%
Richmond upon Thames	41,978	47,416	47%	53%
Lewisham	47,036	36,908	56%	44%
Waltham Forest	52,802	30,089	64%	36%
Merton	33,135	48,515	41%	59%
Kingston upon Thames	25,498	53,833	32%	68%
Southwark	43,123	29,624	59%	41%
Newham	50,359	21,757	70%	30%
Lambeth	46,754	25,250	65%	35%
Haringey	50,796	16,169	76%	24%
Barking & Dagenham	25,951	34,403	43%	57%
Camden	33,497	14,634	70%	30%
Tower Hamlets	24,060	22,569	52%	48%
Hackney	34,201	12,098	74%	26%
Hammersmith & Fulham	36,810	8,906	81%	19%
Westminster	33,332	10,048	77%	23%
Islington	30,622	11,194	73%	27%
Kensington & Chelsea	32,223	7,645	81%	19%

6.8 *Off-street parking availability, example of data from Field Dynamics*

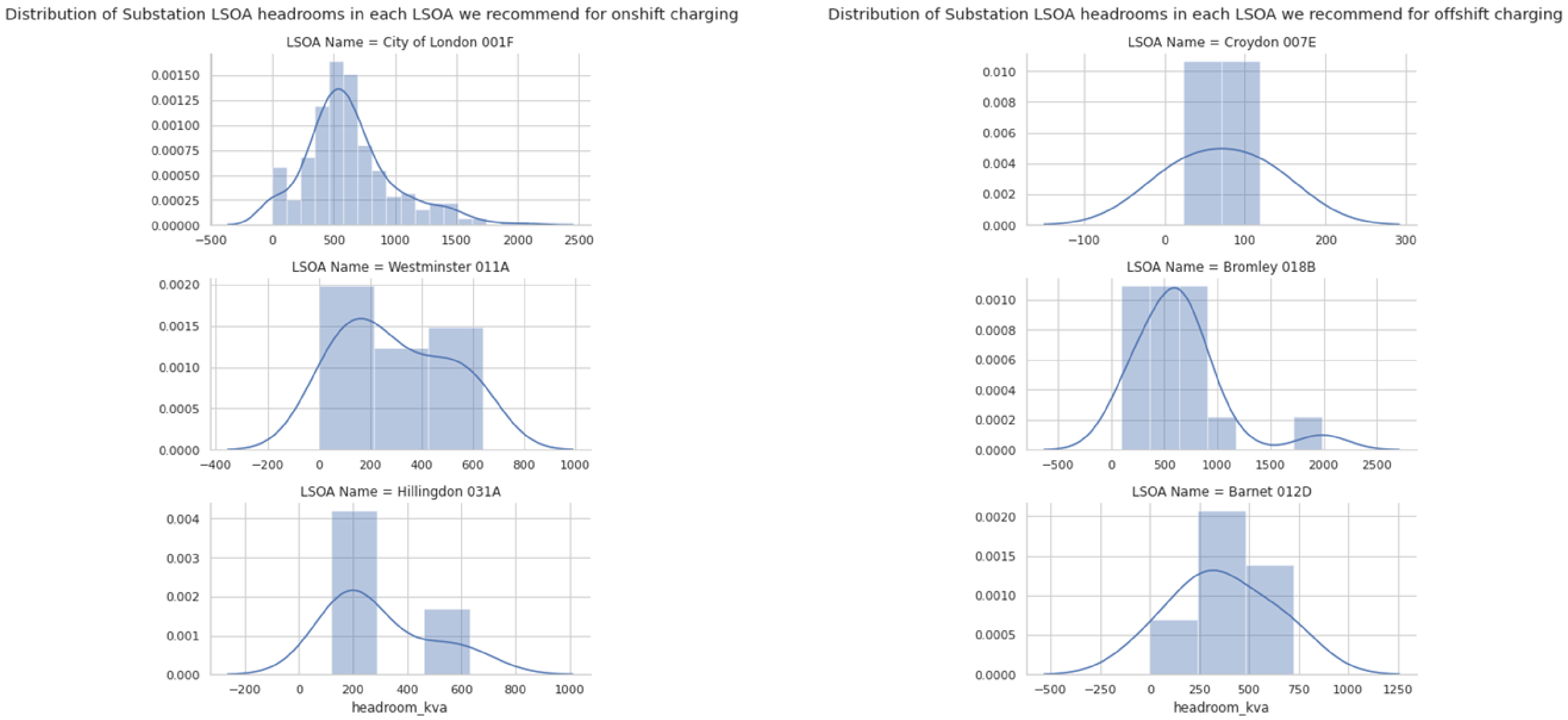
(borough level summary can be viewed at https://onstreetcharging.acceleratedinsightplatform.com/)

Figure 56 – Example of off-street parking data



6.9 Distribution of substation headroom for each LSOA additional charging infrastructure was recommended for

Figure 57 – Distribution substation headroom in selected boroughs



6.10 LSOAs where drivers most frequently had to drive elsewhere and where they had to drive the furthest for on-shift charging, November 2020-January 2021

Table 34 – The LSOAs where drivers most frequently had to travel to other LSOAs to charge

Start LSOA	LSOA Description	Number of charge events originating in LSOA	Average distance travelled to chargepoint (km)
Hillingdon 031A	Heathrow Airport	316	8.72
City of London 001F	City of London	296	4.50
Westminster 018D	Mayfair	284	4.70
Westminster 011A	Marylebone	242	5.08
Westminster 011B	Bond Street	228	4.61
Westminster 013E	North of Piccadilly Circus	183	4.73
Westminster 018C	Pall Mall / North of St James Park	175	4.56
Westminster 019C	Knightsbridge/ Park Lane	175	4.13
Westminster 011E	Marble Arch / Bond Street	158	4.64
Lambeth 036A	Royal National Theatre / Southbank Centre	141	4.03

Table 35 – The LSOAs from which drivers had to drive the furthest in order to charge

Start LSOA	LSOA Description	Number of charge events originating in LSOA	Average distance travelled to chargepoint (km)
Hillingdon 031A	Heathrow Airport	316	8.72
Hounslow 005D	Airlinks Golf and Country Club	65	6.03
Ealing 015E	North Acton	81	5.37
Westminster 011A	Marylebone	242	5.08
Westminster 013D	Fitzrovia	132	4.93
Westminster 013E	North of Piccadilly Circus	183	4.73
Westminster 008D	Baker Street	63	4.73
Westminster 011C	Marylebone	116	4.71
Westminster 018D	Mayfair	284	4.70
Westminster 023E	Victoria station	97	4.65

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9 Sources & Attributions

The following sources have been utilised in the preparation of this deliverable:

- Location of public CPs is provided by Zap-Map
- Hitachi-researched EV vehicle range data (from publicly available third party sources, using Worldwide Harmonised Light Vehicle Test Procedure (WLTP) results, where available)
- Weather data is provided by Dark Sky
- Shapefiles of London Boroughs, Middle Layer and Lower Layer Super Output Areas (MSOAs and LSOAs) sourced from data.gov.uk under Open Government Licence
- Where indicated, map data used in this report is ©kepler.gl ©Mapbox ©OpenStreetMap
- Availability of off-street parking by LSOA, provided by Field Dynamics