Project MADE: Multi-Asset Demand Execution

PassivSystems Initial Modelling and Research Report

Revision history

Version	Change Description	Initials	Release Date
V0.1	Pre-Technical Trial Modelling Final Report	BS	28/09/19

Table of Contents

ABBREVIATIONS

Abbreviation	Term
ASHP	Air Source Heat Pump
BEV	Battery Electric Vehicle
BRISTOL	Buildings, Renewables and Integrated Storage, with Tariffs to Overcome network Limitations
CCC	Committee on Climate Change
DC	Direct Current
DNO	Distribution Network Operator
DSO	Distribution System Operator
EV	Electric Vehicle
FREEDOM	Flexible Residential Energy Efficiency Demand Optimisation and Management
HHS	Hybrid Heating System
LCN	Low Carbon Networks
LCT	Low Carbon Technologies
LV	Low Voltage
MADE	Multi Asset Demand Execution
NIA	Network Innovation Allowance
OLEV	Office for Low Emission Vehicles
PHEV	Plug-in Hybrid Electric Vehicle
PV	Photovoltaics
REX	Range Extender
SOC	State Of Charge
ToU	Time of Use
V2G	Vehicle to Grid
WPD	Western Power Distribution

1 INTRODUCTION

With increasing focus on the decarbonisation of heat and transport, Low Carbon Technology (LCT) asset uptake is expected to rise dramatically. Wide-scale adoption of EVs, low carbon heating and LV network connected solar PV and storage will have a major impact on distribution network loads, requiring increased reinforcement, whilst also increasing the necessity of a secure electricity supply. Past projects have explored each of these LCTs in isolation, but no projects have explored their combined impact. Smart predictive control systems for LCT assets are emerging that could contribute significantly to the efficient operation of networks and the energy system, but could also create unexpected consequences from following energy price signals or optimising consumer demand if not properly aggregated and integrated into the energy system.

The Multi Asset Demand Execution (MADE) project aims to gain insight into the implications of utilising multiple energy assets within a home, and to better understand the feasibility of managing and aggregating these energy assets affordably to reduce network demand, and minimise the requirement for network reinforcement. The project also aims to incentivise LCT uptake by unlocking network and broader energy system value from demand flexibility.

The energy assets considered under this project are:

- Hybrid Heating Systems (HHS) consisting of an electrically-powered heat pump (either air source or ground source) together with a fossil-fuel boiler (oil or gas), which together provide the heating and hot water requirements of the home;
- Solar Photovoltaic (PV) panels;
- Domestic Batteries;
- Electric Vehicle (EV) chargers with bi-directional capability.

This document provides a summary of the work that PassivSystems has carried out under the MADE project to date. This work includes:

- Analysis and utilisation of previous project data sets, in order to infer insight into individual asset use (*See Section 2*).
- High level demand profile modelling, in order to identify issues resulting from uncoordinated asset use and potential solutions to these issues (*See Section 3*).
- Market research, to determine appropriate LCT providers which can facilitate the required control, for use in the MADE project five home trial (*See Section 4*).

2 SUPPORTING DATASETS

PassivSystems have carried out analysis of the data from three previous major projects to facilitate the modelling carried out under the MADE project. These projects were:

- Electric Nation which looked at smart charging of electric vehicles (*See Section 2.1*) ;
- SoLa Bristol which looked at integrating battery storage with PV panels (*See Section 2.2*);
- FREEDOM which looked at hybrid heat pumps (*See Section 2.3*) .

These projects investigated in isolation the individual LCT assets that the MADE project is combining together, so the starting point of the MADE modelling exercise was to understand the conclusions from each of these projects and analyse their datasets to get insight into the MADE scenarios.

2.1 Electric Nation [1]

Electric Nation was an Ofgem funded Network Innovation Allowance (NIA) project hosted by Western Power Distribution (WPD), in partnership with EA Technology, DriveElectric, and Lucy Electric Gridkey. The project aimed to improve understanding of the impact of home electric vehicle charging on electricity distribution networks, and show how demand management using smart chargers could be an alternative to network reinforcement.

The project consisted of three different trials over a period of three years:

- **Trial 1**: Smart charging;
- **Trial 2**: Smart charging + use of an app;
- **Trial 3**: Smart charging + use of an app + time of use incentives.

Two different demand control providers were utilised during the project; GreenFlux and CrowdCharge. Project participants were assigned to one of these two providers on a random basis. GreenFlux participants were provided with an Alfen Eve Single Pro-line smart charge point, and CrowdCharge participants were provided with an APT Security Systems eVolt Smart Wallbox charger.

PassivSystems have carried out extensive analysis of the Electric Nation dataset to understand patterns of EV usage and feed into the overall project designs. In the sections below we provide the details of our analysis and also summarise the project's own conclusions.

2.1.1 Data Overview

A total of 150,105 charging transactions were supplied to PassivSystems in the Electric Nation dataset. For each charging transaction, the following information was supplied:

- Charger ID;
- Vehicle battery capacity;

[1] Electric Nation - The Project, Electric Nation [ONLINE] Available at: http://www.electricnation.org.uk/about/the-project/. [Accessed 28 May 2019].

- Vehicle nominal charge rate;
- Time of connection;
- Time of disconnection;
- Consumed energy.

An estimated charge duration was then calculated for each charging transaction, assuming that the vehicle charged consistently at its nominal charge rate.

$$Estimated\ charge\ duration\ (h)\ = \frac{Energy\ consumed\ (kWh)}{Nominal\ charge\ rate\ (kW)}$$

Of the 150,105 supplied charging transactions, a total of 11,977 were deemed to be anomalous transactions, and were removed from the data set prior to analysis. These anomalous transactions matched one or more of the following errors:

- Energy consumed exceeded vehicle capacity *(3,193 transactions)*;
- Estimated charge duration exceeded connection duration *(4,429 transactions)*;
- Connection duration was less than fifteen minutes *(926 transactions)*;
- Duplicate transaction *(3,765 transactions)*.

A breakdown of the remaining charging transactions is shown below in Table 2.1. These charging transactions were utilised for the analysis discussed in Section 2.1.2.

	Trial 1	Trial 2	Trial 3	Not linked to a Trial	Total
GreenFlux	22,293	19,401	9,628	25,941	77,263
CrowdCharge	25,635	11,895	5,566	17,769	60,865
Total	47,928	31,296	15,194	43,710	138,128

Table 2.1 - Breakdown of Electric Nation transactions used in analysis for the MADE project

2.1.2 Detailed Analysis

The Electric Nation data was analysed in order to gain insight into typical EV charging behaviour, specifically focusing on the following:

- Connection Duration (*See Section 2.1.2.1*);
- Charge Duration (*See Section 2.1.2.2*);
- Time of Connection (*See Section 2.1.2.3*);
- Vehicle State of Charge (*See Section 2.1.2.4*).

Results in this section are obtained through analysis of the Electric Nation data set in its entirety, with the exception of anomalous transactions, as identified in Section 2.1.1. The data has been analysed to ensure that there is consistency between the two demand control providers and across the various trials, in order to validate this approach for the purposes of the MADE project, see Appendix 1.

2.1.2.1 Connection Duration

The analysed Electric Nation charging transactions displayed a wide range of connection durations. Figure 2.1 shows that during the Electric Nation trial, EVs were typically connected for between thirty minutes to four hours, or between nine and sixteen hours, in a single charging transaction. Transactions with short connection durations are likely to represent top-up charges where the EV is needed directly after charging, and the transactions with longer connection durations are likely to represent overnight charging.

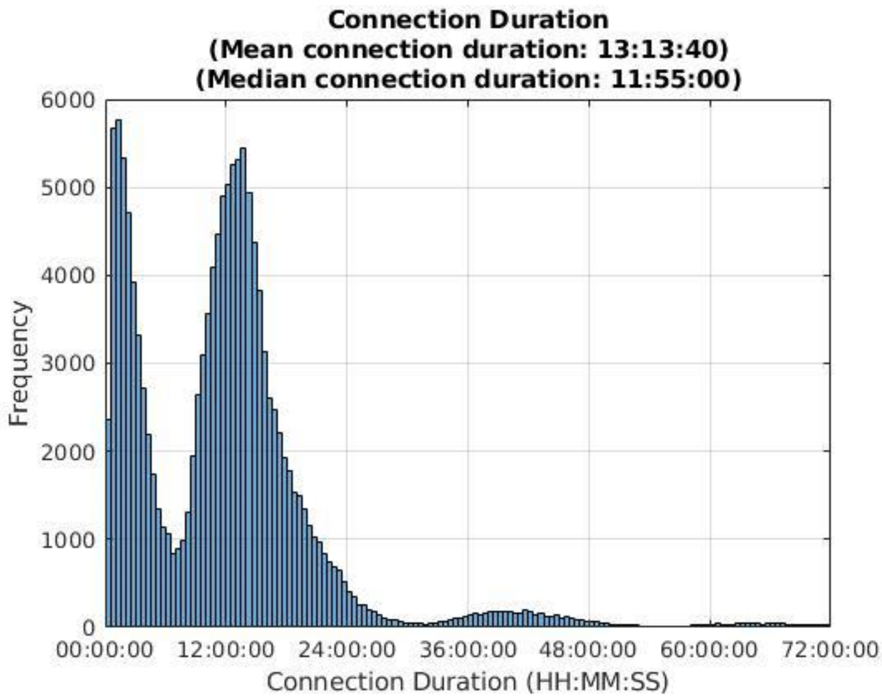


Figure 2.1 - Distribution of connection durations during the Electric Nation trial

Figure 2.2 shows the breakdown of connection durations for Plug-in Hybrid Electric Vehicles (PHEVs), which typically have smaller battery capacity, and Battery Electric Vehicles (BEVs), including Range Extenders (REXs), which in general have a larger battery capacity. It can be seen that both vehicle types display the two peaks observed in Figure 2.1 at shorter connection durations of between 30 minutes and four hours, and larger connection durations of between nine and sixteen hours. In the case of PHEVs, the shorter connection duration peak was slightly larger than the longer connection duration peak, with the opposite true for BEVs.

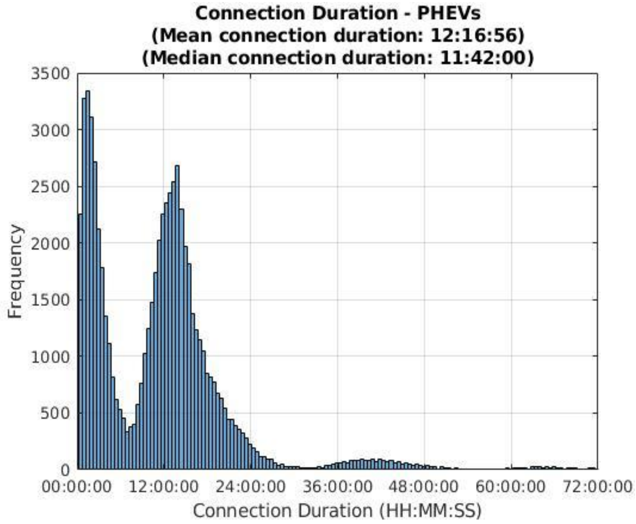


Figure 2.2 - Distribution of connection durations during the Electric Nation trial (PHEV/BEV Breakdown)

2.1.2.2 Charging Duration

Charge duration was estimated as outlined in Section 2.1.1. The estimated charge duration for the Electric Nation charging transactions was typically less than three hours, as can be seen in Figure 2.3.

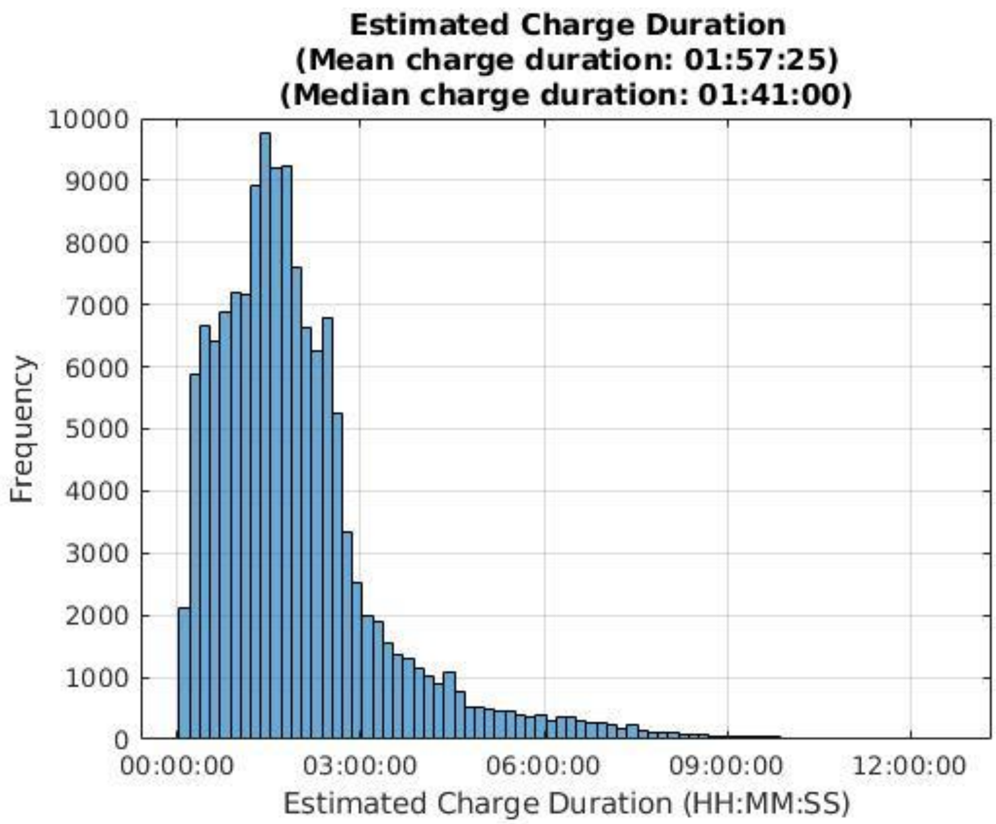


Figure 2.3 - Distribution of estimated charge durations during the Electric Nation trial

Figure 2.4 shows the breakdown of charge durations for PHEVs and BEVs. It can be seen that all estimated charge durations for PHEVs are less than four hours, with the vast majority less than three hours. Whilst the majority of BEV estimated charge durations are also less than three hours, there are a greater proportion of charges lasting greater than three hours than represented in the overall distribution shown in Figure 2.3. Based on these observations, charging duration should be considered in relation to vehicle capacity for the purposes of project MADE.

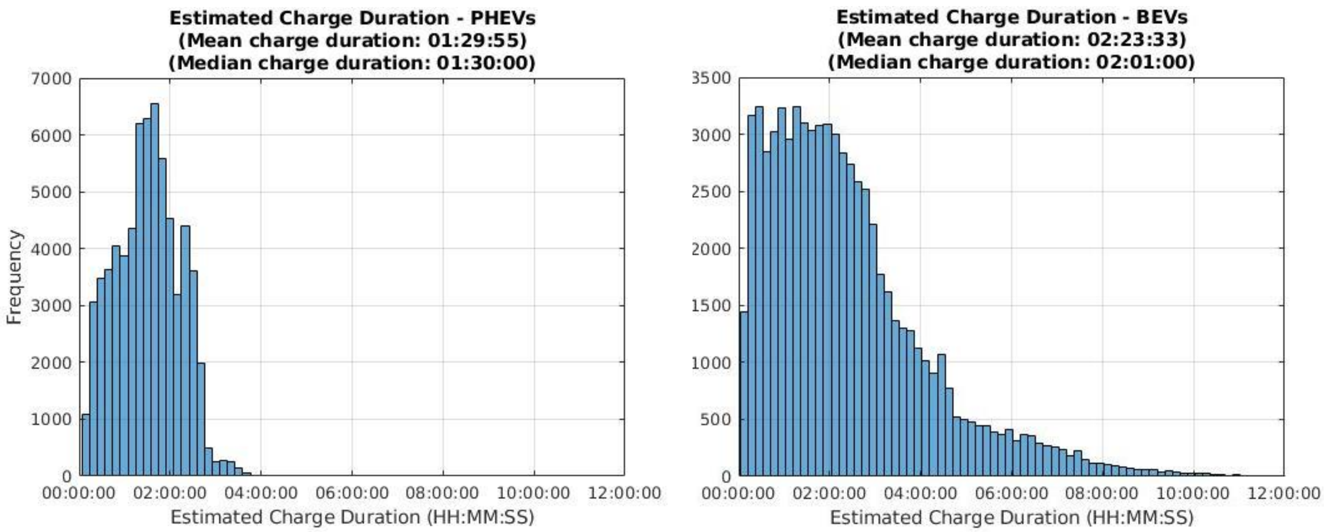


Figure 2.4 - Distribution of estimated charge durations during the Electric Nation trial (PHEV/BEV Breakdown)

Through discussion between the MADE project partners, it has been agreed that EV modelling considered under the MADE project will be based on a 33 kWh, 7 kW battery, since this was the most common EV battery type found in the Electric Nation dataset. There were 20,445 charging transactions matching an EV of this description contained in the data. Figure 2.5 shows the distribution of estimated charge durations during the Electric Nation trial for vehicles with a 33 kWh, 7 kW battery. Since a battery of this nature would take approximately 4 hours and 43 minutes to fully charge, Figure 2.5 suggests that the vehicles considered are typically not fully charging, with a mean charge duration of just over two hours.

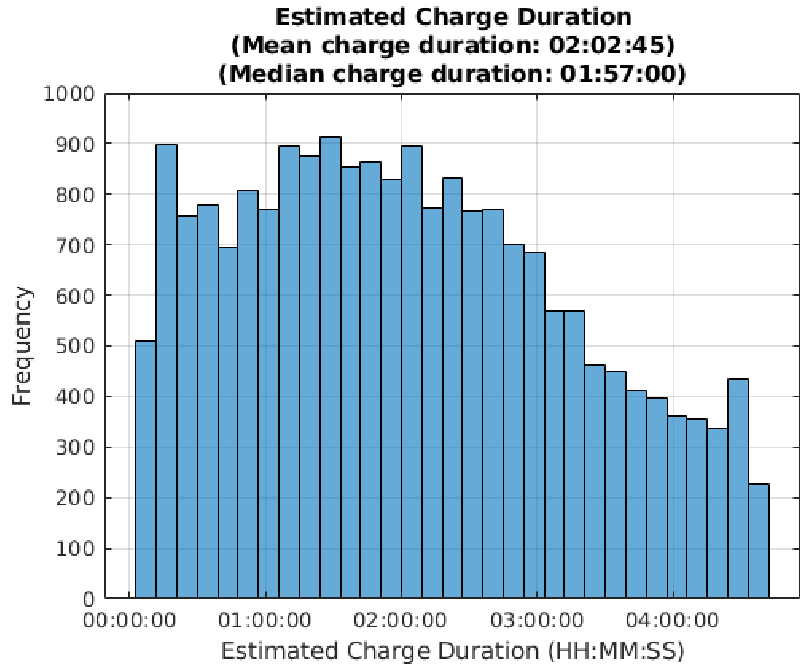


Figure 2.5 - Distribution of estimated charge duration for 33kWh, 7kW vehicles during the Electric Nation trial

During Electric Nation, vehicles did not typically charge for the whole duration that they remained connected to the charger. Figure 2.6 shows that vehicles were typically only charging for less than thirty percent of the time they spent plugged in. This suggests that there is a large amount of scope for demand management of EV charging to be executed.

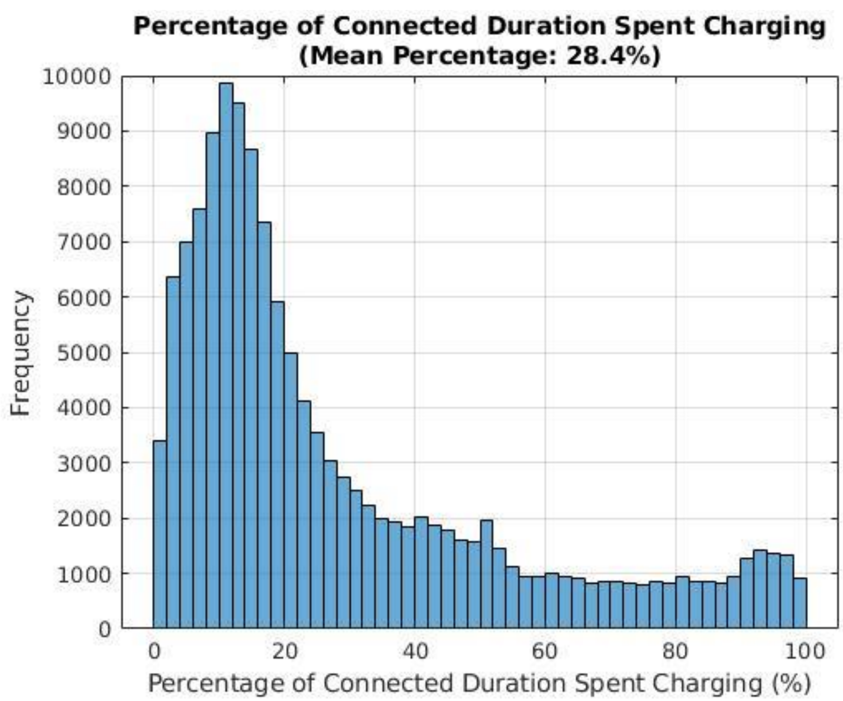


Figure 2.6 - Distribution of percentage of connection duration spent charging during the Electric Nation trial

2.1.2.3 Time of Connection

During the trial, vehicles were primarily plugged in to the charger in the evening. Figure 2.7 shows that vehicles were most commonly plugged in between 17:00 and 19:30. This timing is likely to coincide with heating demand, supporting the requirement for demand management.

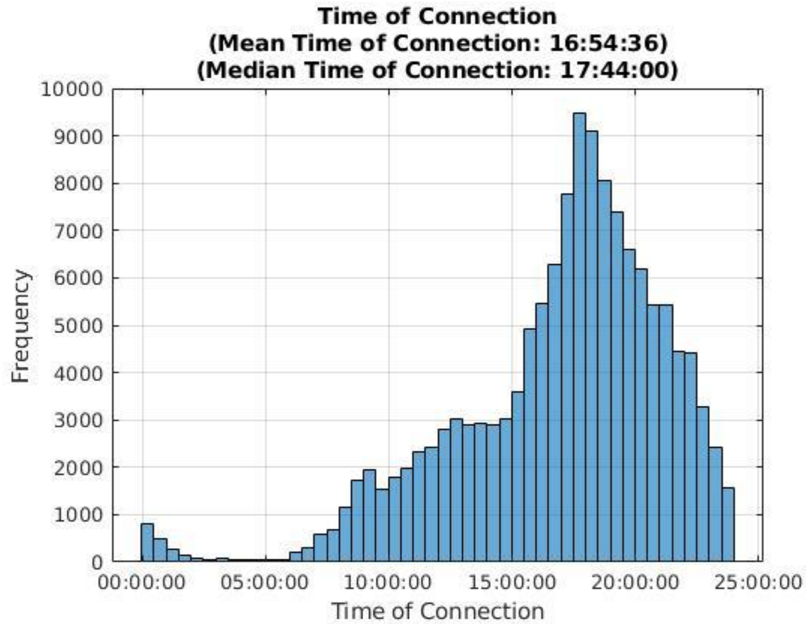


Figure 2.7- Distribution of time of connection during the Electric Nation trial

Figure 2.8 shows connection duration against time of connection. It can be seen that connection durations of less than seven hours occurred throughout the day, predominantly between 07:00 and 20:00. Longer connection durations of between seven and fourteen hours typically occurred during the evening, after 16:00.

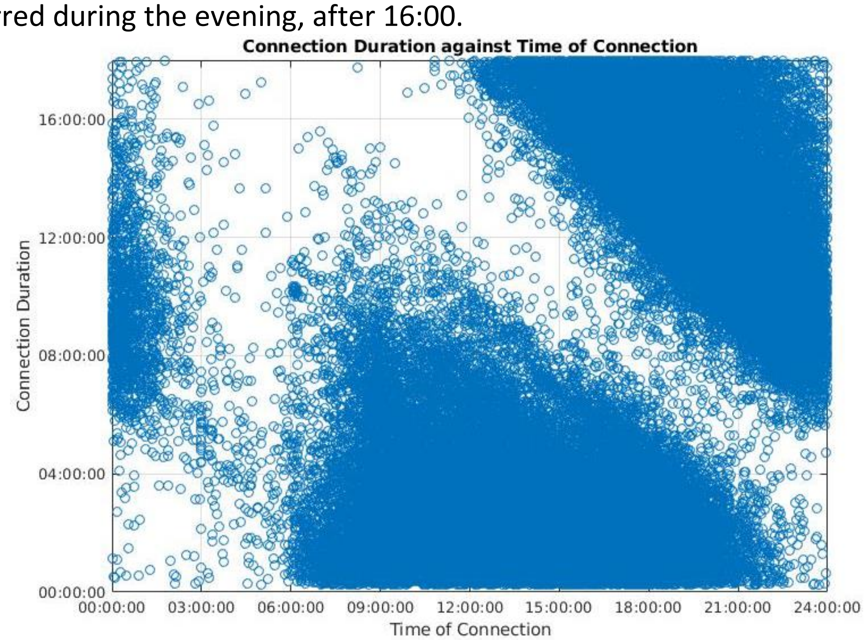


Figure 2.8 - Connection duration against time of connection during the Electric Nation trial

2.1.2.4 Vehicle State of Charge (SOC)

There was a large amount of variation in battery SOC increase per charging transaction during the trial, as can be seen in Figure 2.9. This suggests that vehicles are likely to have a wide range of remaining SOC upon connection. A small peak can be seen between 69% and 88% SOC.

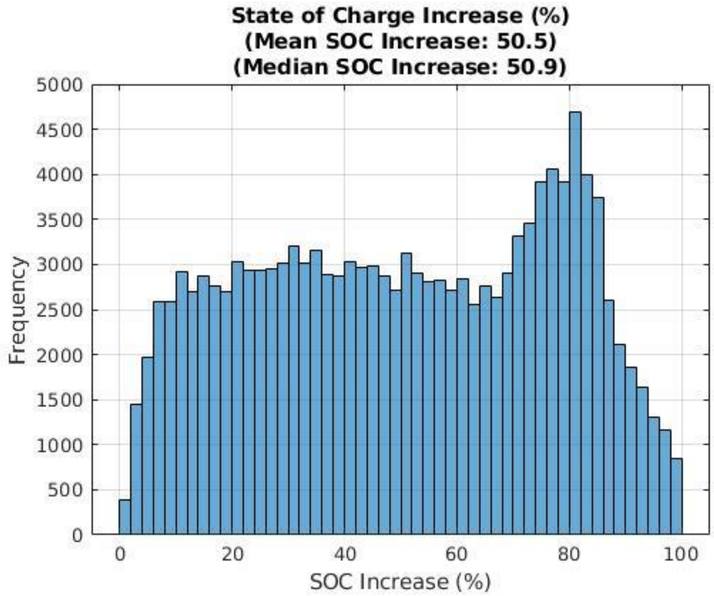


Figure 2.9 - Distribution of state of charge increase during the Electric Nation trial

Figure 2.10 shows the breakdown of state of charge increase for PHEVs and BEVs. It can be seen that the peak in overall distribution, as shown in Figure 2.9, is entirely down to PHEVs, which typically charge between 69% and 88% in a single transaction. This high state of charge increase is expected due to the hybrid nature of the PHEVs eliminating range anxiety, therefore EV drivers allowing their vehicles to reach a lower state of charge . BEVs however typically charge less than 60% in a single transaction.

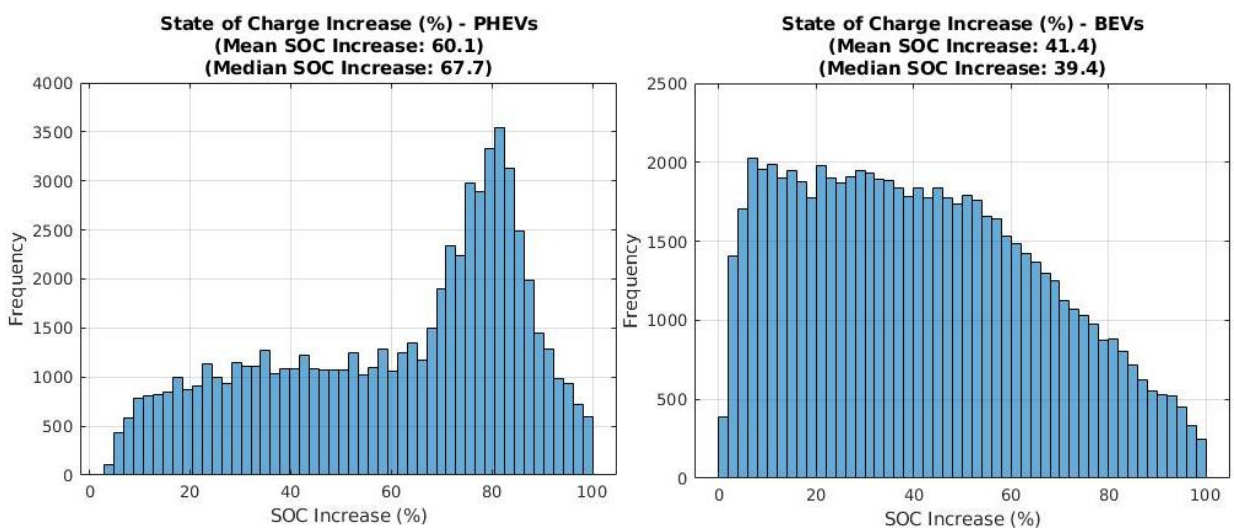


Figure 2.10 - Distribution of SOC increase during the Electric Nation trial (PHEV/BEV Breakdown)

2.1.3 Electric Nation Dataset Conclusions

2.1.3.1 PassivSystems Analysis Conclusions

In summary, the following observations can be drawn from Passiv's analysis on the Electric Nation dataset:

- EVs were typically connected for between thirty minutes to four hours, or between nine and sixteen hours, in a single charging transaction;
- The estimated charging duration per transaction was typically less than three hours;
- EVs were most commonly plugged in to the charger in the evening, between 17:00 and 19:30;
- There was a large amount of variation in battery state of charge increase per charging transaction, particularly for BEVs. BEVs typically underwent a SOC increase of less than 60%;
- The most common EV battery configuration found in the dataset was a 33kWh battery able to charge at 7kW.

2.1.3.2 Additional Electric Nation Project Conclusions

The following conclusions have also been evidenced by the Electric Nation project team:

- Trial data shows that there is scope for flexibility, particularly during the evening peak which aligns well with highest network demand;
- Demand management is technically feasible, and is acceptable to the majority of trial participants;
- Trial data shows that Time of Use (ToU) incentives appear to be highly effective at moving demand away from the evening peak;
- Without management, ToU incentives could lead to large peaks when electricity becomes cheap;
- Smart charging can:
    - Support the introduction and management of ToU based charging;
    - Provide a means to manage any negative consequences of mass uptake of ToU incentives.

2.1.3.3 Overall Conclusions

The analysis of the dataset discussed in Section 2.2.2 of this report coupled with the Electric Nation project conclusions show there is clear scope for demand management, particularly during the evening peak. The trial also demonstrated that ToU incentives were effective in moving demand management from the evening peak, however trial data suggests that coordinated control between households may be required to manage the consequences of mass uptake of ToU incentives and prevent the introduction of new charging peaks. Overall, these conclusions provide strong support for MADE control. The Electric Nation data also provides a good foundation for the generation of a typical EV charging profile to feed into the MADE modelling work.

2.2 SoLa Bristol [2]

SoLa Bristol (Buildings, Renewables and Integrated Storage, with Tariffs to Overcome network Limitations) was a project hosted by WPD, in partnership with Bristol City Council, the University of Bath, Knowle West Media Centre, and Siemens, funded through Ofgem's Low Carbon Networks (LCN) Fund. The project aimed to address the technical constraints that DNOs (Distribution Network Operators) expect to arise on Low Voltage (LV) networks as a result of the adoption of solar PV. In particular, the project considered how battery storage could assist with network management, in addition to saving customers money on their energy bills.

SoLa Bristol involved twenty six homes, which had 4.8 kWh of battery storage installed alongside solar PV panels ranging from 1.5 kWp to 2 kWp. The PV panels were connected directly to the battery using a 2kW DC/DC converter, with a 2kW inverter to convert DC power to AC. Each home also had a DC micro grid installed that ran from the battery, providing lighting and USB charge points. In addition, each home was connected to the local electricity network to allow excess energy to be exported to the grid at peak times. Participants were provided with a pseudo variable tariff, which encouraged electricity use at times of high PV generation and battery use when the network was heavily loaded. During the project, the battery was shared between the participant and the DNO. The DNO was able to charge and discharge the battery to help with network management.

PassivSystems have conducted analysis of the SoLa Bristol dataset to identify whether it is suitable for use in the MADE modelling to represent typical battery and solar PV operation.

2.2.1 Data Overview

Data for eleven homes has been analysed, running from December 2014 to February 2016. For each home, minutely and 15-minutely data was supplied for the following:

- Battery current (A);
- Battery voltage (V);
- Battery temperature (°C);
- PV Current (A);
- Household AC Current (A);
- Household AC Voltage (V);
- Household AC Power (kW);
- Current flow between DC and AC (A).

The eleven included homes and their corresponding load types can be seen in Table 2.2. The load types are described as follows:

[2] SoLa Bristol, Western Power Distribution [ONLINE] Available at: https://www.westernpower.co.uk/projects/sola-bristol. [Accessed 28 May 2019].

- Normal: Considered to be similar to a typical national-wide profile, usually with a high evening peak;
- High daily load: High demand in the daytime instead of high demand peak in the evening;
- Economy 7: Properties with a dual tariff system, often high overnight demand.

Home Number	Load Type
06	Economy 7
07	Economy 7
13	Normal
15	High daily load
16	Normal
20	Normal
21	Normal
22	Normal
23	Normal
24	Normal
26	High daily load

Table 2.2 - Homes included in the SoLa Bristol dataset and their load types

PV power was not included in the data set, only PV current. However since the PV and battery systems were directly coupled on the DC side of the inverter, PV voltage is assumed to be the same as battery voltage. Therefore, PV power has been calculated as the product of PV current and battery voltage. It can be seen from Figure 2.10 that the calculated PV power aligns with examples of PV power for homes 15 and 16 on the 15th April 2015 from the SoLa Bristol Final Report[3], providing confidence in this approach.

[3] SoLa Bristol SDRC 9.8 Final Report, Western Power Distribution, January 2016

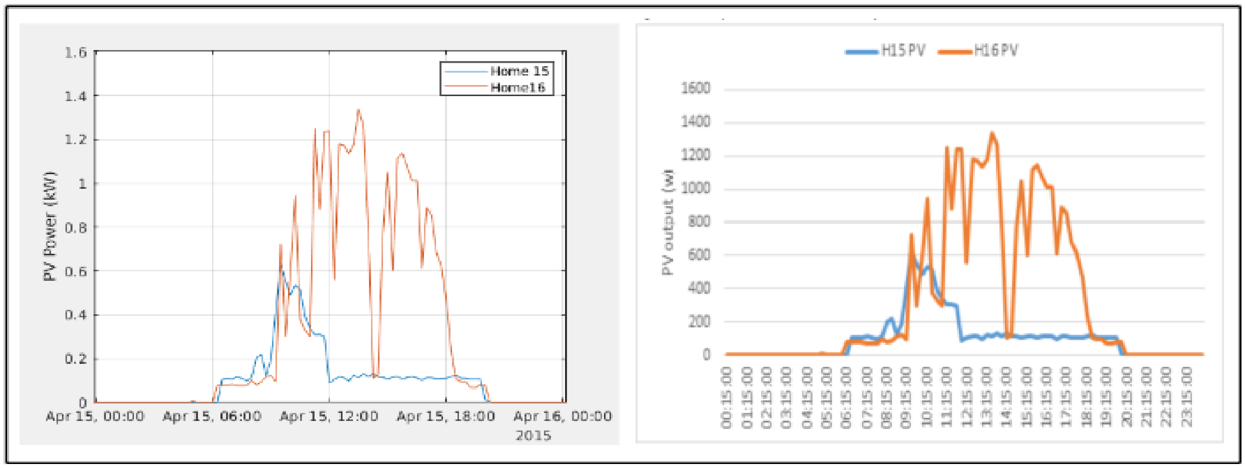


Figure 2.10 - Calculated PV power against actual PV power for homes 15 and 16 on 15th April 2015

2.2.2 Data Analysis

2.2.2.1 PV Generation

PV generation was analysed for all eleven homes. It can be seen from Figure 2.11 that, as expected, PV generation is higher across the summer and lower during the winter. It can also be seen that there are a number of gaps in the PV generation data. Some of the homes are missing PV readings from towards the end of the summer months onwards.

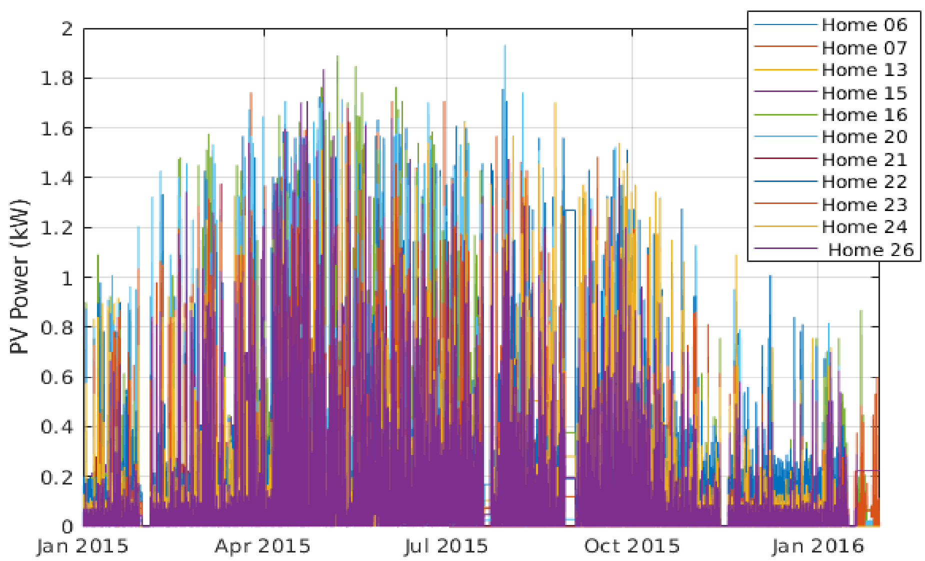


Figure 2.11 - PV generation across the SoLa Bristol data set for all eleven homes

It can also be seen from the data that a number of homes (13, 15, 21, 22 and 24) display much lower PV generation than expected for a 1.5 - 2kWp solar installation, remaining relatively consistent throughout the day, as displayed in Figure 2.12 which shows PV generation on the 19th June 2015. It can also be seen from this Figure that a sharp change in PV power can be observed at the start and end of each day. This is not in line with what we would typically expect to see, and may potentially be down to some sort of system fault.

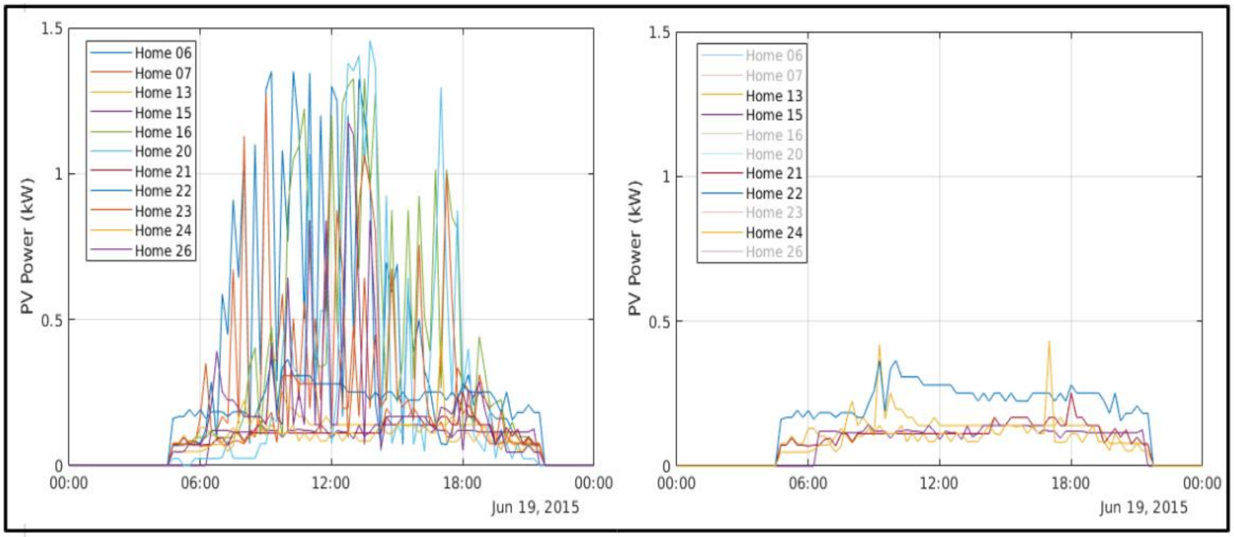


Figure 2.12 - PV generation on 19th June 2015 for a selection of homes

2.2.2.2 Battery State of Charge (SOC)

During the SoLa Bristol trials, upper and lower thresholds were set for the battery state of charge, outside of which the battery was not able to freely charge and discharge, as can be observed in Figure 2.13. Above the maximum SOC threshold, the battery was reserved for DNO use, should they require to push excess power to the battery. However the minimum SOC threshold worked slightly differently, and was the lower limit for all standard battery operation. The system would only support a pull request from the DNO if there was sufficient spare capacity above the minimum state of charge. The minimum SOC threshold was in place to support the project aim of "Keeping the lights on" during a power outage.

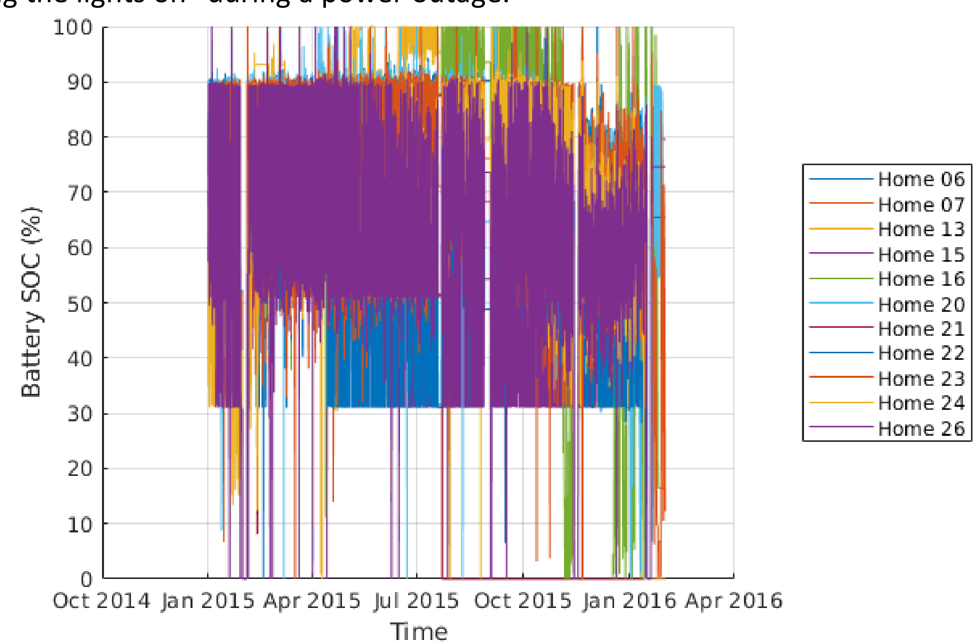


Figure 2.13 - Battery SOC across the SoLa Bristol data set for all eleven homes

These battery state of charge constraints lead to oscillations in battery state of charge around the limits of operation, as can be seen in Figure 2.14 for Home 20. These oscillations are due to the battery entering an import-export cycle to prevent the state of charge violating the boundary conditions that are being imposed. We can again see clearly from this figure that the battery is unable to reach anywhere near 0%, with a lower state of charge threshold of around 50%.

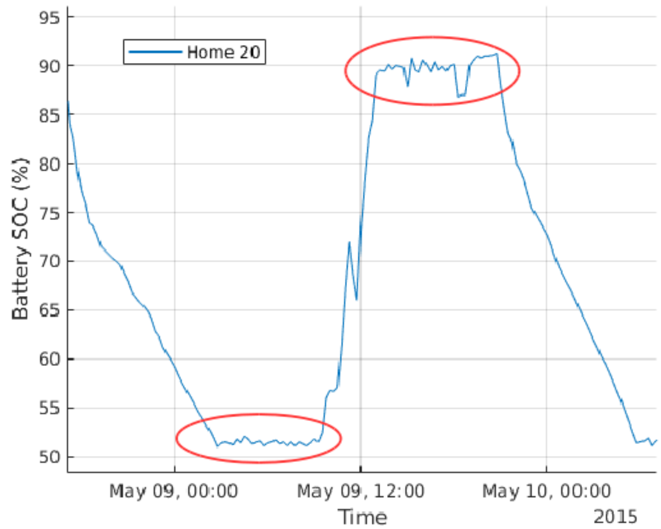


Figure 2.14 - Battery SOC oscillations at the SOC thresholds for Home 20 on 9th May 2015

It can also be observed from the data that some homes experience a reduction in state of charge over the summer months, an example of which is shown in Figure 2.15 for Home 22. This is not in line with expectations, since it would be expected that increased PV generation across the summer months combined with typical decreased consumption during these months would lead to a higher battery state of charge in general.

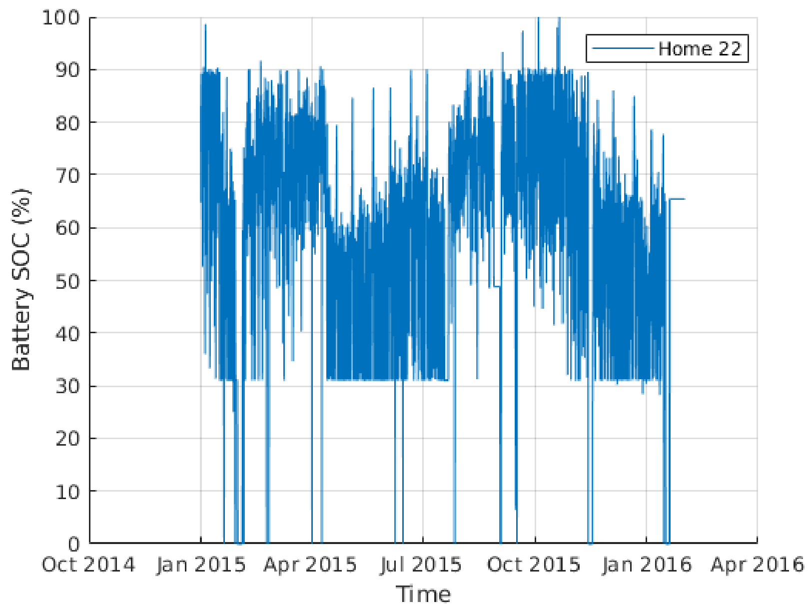


Figure 2.15 - Battery SOC for Home 22

Further analysis of Home 22 has been conducted across these summer months that demonstrate a lower than expected battery state of charge. It can be seen from Figure 2.16 there there is no reduction in PV generation across this time period that would explain the reduced SOC. It has also been investigated whether this reduction in SOC was due to an increase in battery temperature leading to a reduction in battery performance. It can be seen from the third plot in Figure 2.15 that the battery temperature was in fact higher in August, when the battery SOC had recovered to a higher value, than in May, when reduced SOC can be observed. Therefore the reduction in SOC cannot be explained by an increase in battery temperature.

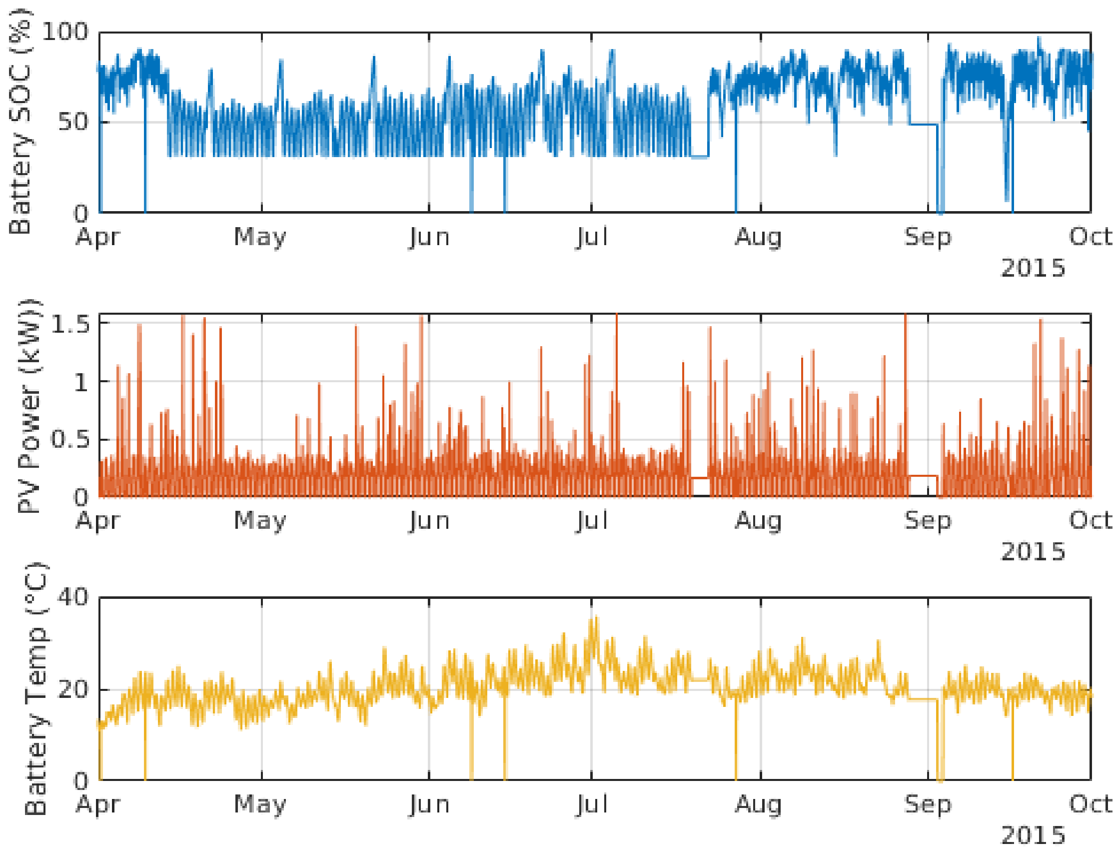


Figure 2.16 - Investigation into the reduced state of charge displayed for Home 22 over the summer months

It can therefore be concluded that this observed reduction in battery state of charge is likely due to DNO control over the battery and a variation in the implemented control strategy.

2.2.3 SoLa Bristol Dataset Conclusions

Due to DNO control over the battery during the project, with varying state of charge limits throughout the year, the SoLa bristol data is not a typical representation of domestic battery use across the year, and it is therefore difficult to deduce insight into typical seasonal behaviour from the data.It is therefore not ideal for direct use in order to represent a typical annual household battery profile for use in Project MADE. Additionally, gaps in solar data, alongside a lack of orientation data regarding the installations, mean that the solar data is not ideal for use in forming typical PV generation data for use in the MADE modelling. Solar generation profiles for the MADE modelling have therefore been determined through analysis of relevant homes from Passiv's solar monitoring portfolio, as discussed in Section 2.3.

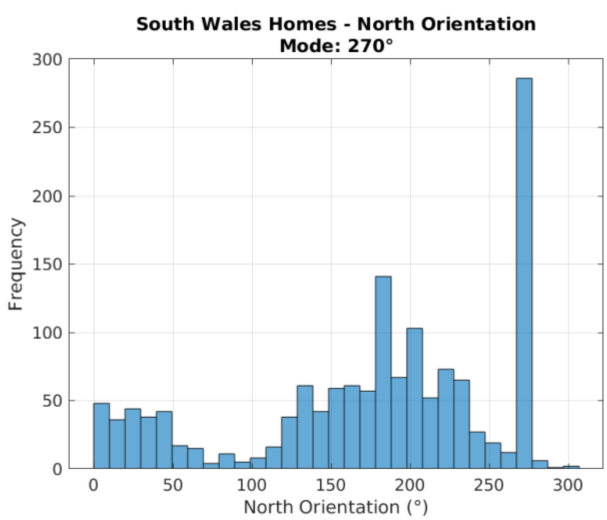
2.3 PassivSystems' Solar Monitoring Portfolio

PassivSystems monitor over 40,000 solar installations across the UK. Analysis has been conducted on this solar dataset to determine suitable representative solar generation profiles for use in the MADE modelling.

The dataset was first analysed as a whole to determine the typical kWp values and orientations contained in the dataset. Analysis was also performed only considering South Wales homes, since this is a key area of interest for Project MADE and FreeVE. A summary of these results can be seen below in Table 2.3.

Region	Parameter	Mean	Mode
South Wales (1,458 installations)	**North Orientation**	See Figure 2.17 for distribution	270.00°
	Horizontal Orientation	31.51°	30.00°
	kWp	4.07 kWp	4.00 kWp
United Kingdom (44,873 installations)	**North Orientation**	See Figure 2.18 for distribution	180.00°
	Horizontal Orientation	32.14°	30.00°
	kWp	3.27 kWp	4.00 kWp

Table 2.3 - PassivSystems' solar monitoring portfolio summary statistics



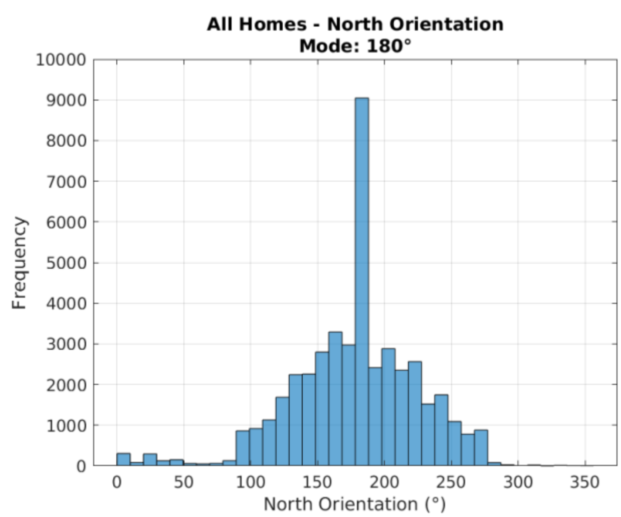


Figure 2.17 South Wales homes north orientation distribution

Figure 2.18 All homes north orientation distribution

The customer/household types[4] that have been agreed by all project partners for use in the MADE modelling have solar installations of 1, 2 and 4 kWp. A number of suitable solar generation profiles from solar installations of these sizes were thus extracted from the data set, taking into account orientation parameters drawn from the analysis presented above, for use in Passiv's modelling under the MADE project. These profiles were also provided to Everoze for use in their domestic level techno-economic modelling.

2.4 FREEDOM [5]

FREEDOM (Flexible Residential Energy Efficiency Demand Optimisation and Management) was a NIA funded cross-sector collaboration between electricity and gas distribution networks Western Power Distribution and Wales & West Utilities, who engaged PassivSystems to deliver the project, supported by partners Imperial College, Delta-ee and City University. The aim of the project was to investigate the network, consumer and broader energy system implications of high volume deployments of hybrid heating systems.

The FREEDOM project yielded a valuable dataset of the hybrid heating system performance across 75 trial homes. However, the dataset is not directly suitable for MADE purposes as the homes were on a mains gas supply, and not receiving RHI (Renewable Heat Incentive) payments, so the heat pumps were not utilised as much as would be expected in a future decarbonised heating scenario (which is where MADE's focus is). Our approach is to use the insight from FREEDOM to develop models that extrapolate to this scenario using PassivSystems' built-in building physics model.

Following the FREEDOM project, PassivSystems have developed an annual forecasting tool, enabling the gas and electricity demands of a hybrid heating system to be modelled, in order to provide heat pump demand profiles for use in the MADE modelling. The tool utilises Passiv's in-depth knowledge of heat pump operation, developed through the FREEDOM project, in conjunction with weather data, user defined schedules/setpoints, learnt thermal properties of the house and tariff information to look ahead in time and predict how the heat pump and boiler will behave in tandem to deliver householder comfort whilst minimising the cost. Energy predictions for each half hourly period within a given year are then returned, estimating the performance of a particular FREEDOM home in the MADE scenario.

Using this annual forecasting tool, a selection of optimised 2018 heating profiles were generated, based on appropriate FREEDOM homes for use in the MADE modelling. These profiles were also provided to Everoze for use in their modelling. A total of ten FREEDOM homes were used to generate the heat profiles. For each home, profiles were generated using the following methods:

[4] MADE Project: Customer Segmentation, Delta-ee, May 2019

[5] FREEDOM, Western Power Distribution [ONLINE] Available at: https://www.westernpower.co.uk/projects/freedom. [Accessed 28 May 2019].

- **Use Real Set Points:** The profiles generated via this method utilise actual set points for each particular home, as set by the user, therefore these may vary throughout the year as the user makes changes. In this case, optimisation will take into account future overrides carried out by the user, which shouldn't actually be known about at the time of optimisation.
- **Use Home Occupancy Schedule:** Profiles generated through this method will use the actual home occupancy schedules, and will not take into account manual overrides in the optimisation.
- **Use Altered Day-time Occupancy Schedule:** Profiles generated through this method will use altered home occupancy schedules, which assume day time occupancy.

Through the FREEDOM project, Passiv have also gained knowledge on consumer acceptance of hybrid heating system operation, and therefore what demand management interventions may be acceptable to consumers. This will help to shape the MADE control strategy.

3 MODELLING

PassivSystems have carried out an internal programme of modelling to explore the interrelations between the low carbon assets. The approach is broadly similar to Everoze's Domestic-Level Modelling but is more closely tied with PassivSystems models, that will be used in the field trial. We were also keen to understand the more detailed relationships between the assets and explore directly some of the elements of coordinated control that are going to be tested live in the field trial.

3.1 Modelling Approach

The modelling approach first involved generating typical demand profiles for the technology assets considered under the MADE project when operating in isolation. These baseline individual profiles were then layered to obtain a typical whole household system demand profile, which was then analysed in order to gain awareness of potential demand problems, and to obtain insight into potential flexibility which could offer a solution to these problems.

The individual profiles utilised in the modelling were generated as shown in Table 3.1. The asset configurations used in the modelling align with the high demand, high EV use (Commuter) customer type used in Everoze's domestic level techno-economic modelling. The modelling was carried out across a whole year on a half-hourly basis, using 2018 data, and utilises the variable tariff supplied by Everoze, matching the tariff utilised in Everoze's modelling.

Profile	Source	Modelling asset configuration
Heat pump demand	Example annual profiles of heat pump demand for a high, medium and low demand home were generated by utilising FREEDOM data for relevant homes alongside Passiv's annual forecasting tool. It should be noted that when using this tool to optimise a hybrid heating system, the heating profiles are not yet optimised against solar generation. Forecasting was performed in line with the annual cost of energy supplied by Everoze.	Heating system: Hybrid heating system (air source heat pump + gas boiler) Power: 2kW Heating demand: High Daytime occupancy: Yes Assumptions: Optimised based on input tariff using Passiv's annual forecasting tool, as discussed in Section 2.4.
Solar generation	Example annual solar generation profiles were extracted from relevant homes from Passiv's solar monitoring portfolio.	kWp: 4kWp North orientation: 180° Horizontal orientation: 35°
EV charging	Example annual EV charging demand	EV battery capacity: 33kWh

demand	profiles were supplied by Delta-ee. These profiles were based on the Electric Nation dataset, alongside responses to Delta-ee's MADE survey around EV charging habits.	Charge power: 7kW EV demand: High - 'Commuter' use case including weekday commute and weekend visits to friends and family (See Figure 3.1 for EV usage pattern). Charging assumptions: Unmanaged EV charging - the vehicle charges whenever it is plugged in and has spare capacity.
Base household electricity consumption	Example annual base household consumption data was supplied by Delta-ee. This data was drawn from the Powering the Nation dataset.	Electrical demand: High
Battery Demand	Battery demand was simulated using solar generation and total consumption, alongside Passiv's knowledge of battery operation and discussions with the battery manufacturers.	Capacity: 10kWh Inverter power rating: 3.3kW Charging assumptions: Battery charges when there is excess solar generation and discharges to meet excess household consumption.

Table 3.1 - Data sources for the individual profiles used in the modelling

Figure 3.1 shows the commuter EV usage pattern which has been used in the modelling, showing when the EV is connected to the chargepoint. For this usage pattern, it has been assumed that the EV is connected to the charger for the duration of time spent at the household.

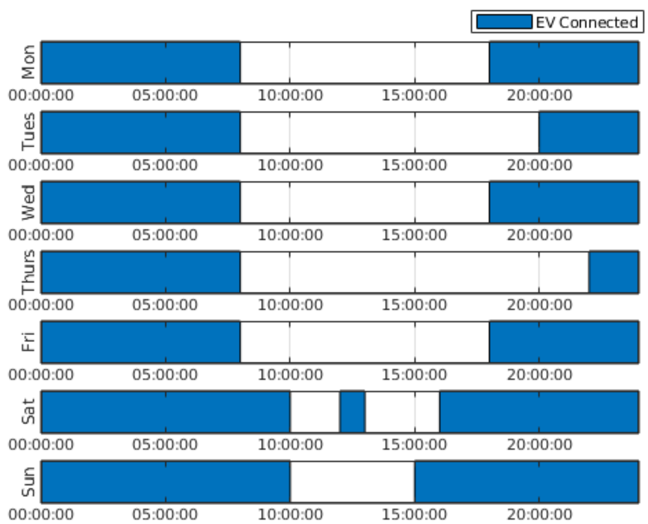


Figure 3.1 - Commuter EV usage pattern used in the modelling, showing when the EV is connected to the chargepoint.

3.2 Whole Household System Demand Modelling

The individual demand profiles discussed in Section 3.1 were then used to generate a whole system househouse profile. Heat, EV charging and base electricity consumption profiles were combined to generate total household demand. This total demand was then utilised in conjunction with solar generation to simulate battery power, before the remaining required grid import was calculated.

3.2.1 Baseline Profile

For the baseline case we consider un-coordinated low carbon assets. The modelled baseline household grid import demand (including heat pump heating) can be seen below in Figure 3.2. The heat pump provides as much of the heating as possible (with the boiler topping up only in the coldest weather), but does not react to solar generation or coordinate with the battery; it does however shift demand against the varying ToU tariff. The battery charges when there is excess solar and discharges to meet excess household consumption (including the heat pump which is not distinguished from other electrical load). The following observations can be made:

- The annual net total cost of electricity is £1,598. This consists of £1,620 in import costs and £22 in export revenue.
- As expected import demand is higher during the winter months and lower over the summer. This is primarily down to increased heating and reduced solar generation during the winter.
- Export occurs only during the summer months.

To allow for comparison with Everoze's base case modelling, household grid import demand has also been generated for the case with no battery storage, as can be seen in Figure 3.3. This matched closely to the import profile generated by Everoze for the "High, Commuter" scenario, where a net total cost of £1,727 is comparable to the Passiv model cost of £1,721. However, for the duration of this report, the baseline case is assumed to be that described by Figure 3.2, with the inclusion of a battery.

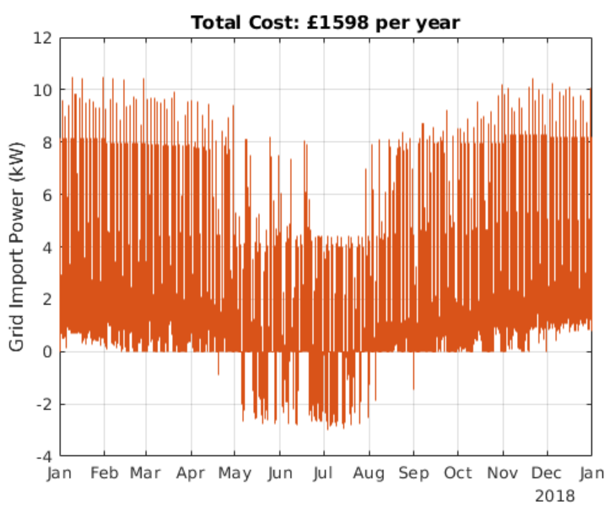


Figure 3.2 - Baseline grid import profile (with battery)

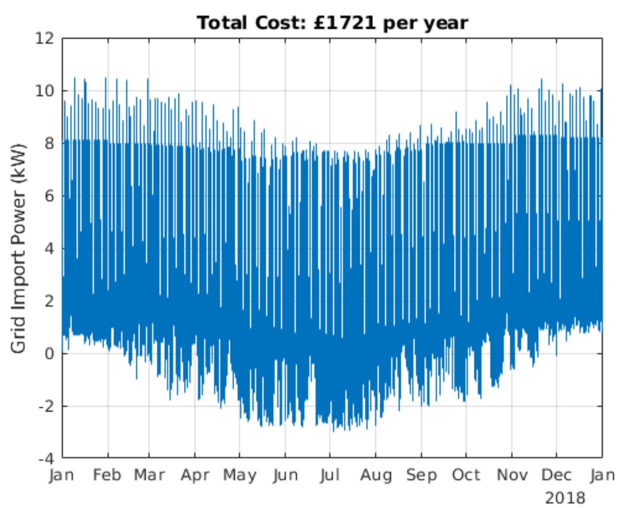


Figure 3.3 - Grid import profile (No battery)

Figure 3.4 shows the modelled baseload household demand on a typical winter day. It should be noted that 'Heat Power' displayed on the graphs in this section represents the electrical power consumed by the heat pump. The following observations can be made:

- Due to the nature of the EV Commuter use profile, EV charging is likely to fall during times of increased electricity import costs, corresponding to times where there is high demand on the network. This timing, coupled with the high EV charges rates, mean that this is both expensive for the consumer and likely to lead to potential network problems.
- EV charging is a significant load compared to other household loads; EV charge power can reach up to 7kW, whilst heat pump power is constrained to 2kW, battery charge power is constrained to 3.3kW and base household electricity consumption has a maximum of 1.8kW over the year. This suggests that simply shifting the EV charging to a different time or postponing the operation of other energy assets within the home whilst the EV is charging is not likely to be a sufficient solution to mitigate potential network overloads if high EV uptake occurs. Instead, one possible solution includes inter-home coordination, where the EV load of one household could be compensated by the delaying of EV charging or switching to gas boiler use in a combination of other households. Alternatively, another potential solution includes a constraint on EV charge rates. Reducing the EV charge rate would potentially make it possible to compensate for the EV charging load through intra-home coordination of assets, since the loads would be more comparable.
- Due to low solar generation coupled with the assumed simplistic charging behaviour (charging when there is excess solar generation, discharging when there is excess household consumption), the battery is used very little over the winter.

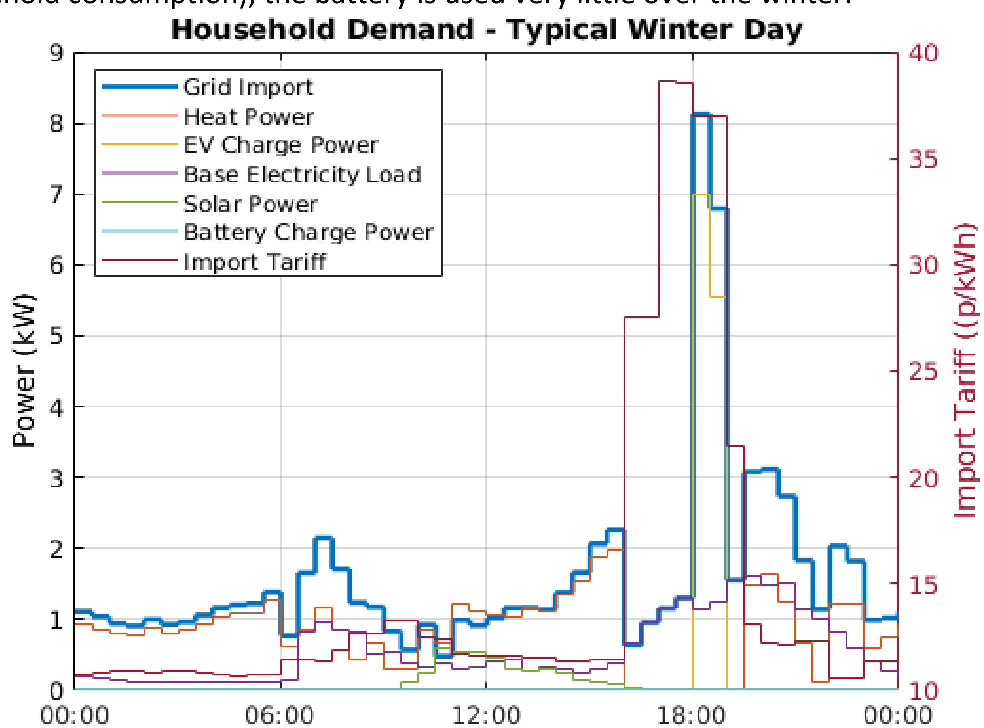


Figure 3.4 - Baseload household demand on a typical winter day (22nd January 2018)

Figure 3.5 shows the modelled baseload household demand on a typical summer day. The following observations can be made:

- Due to increased solar generation combined with reduced household demand, the battery is used much more heavily than during the winter.
- EV charge power remains a significant load, however during the summer this load can be partially met by the battery.
- Battery operation combined with significantly decreased heating demands leads to significantly reduced import demands over the summer months.

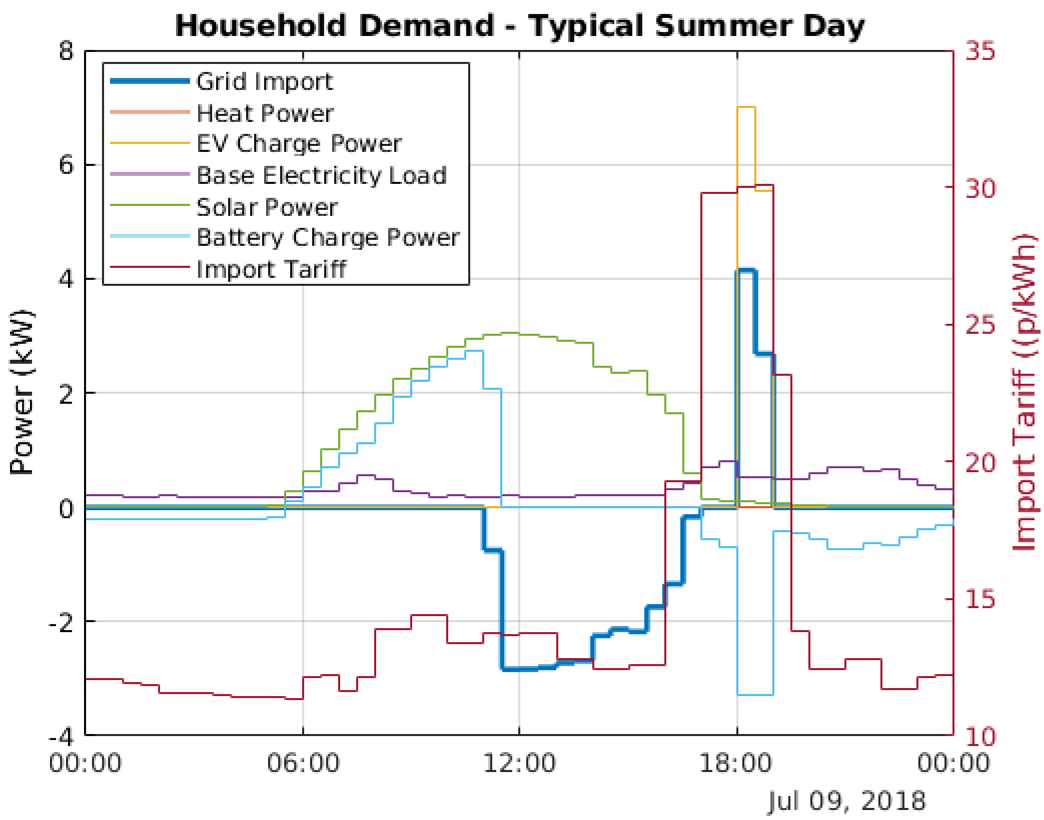


Figure 3.5 - Baseload household demand on a typical summer day (9th July 2018)

Figure 3.6 shows the modelled baseload household demand on some example shoulder season days. The following observations can be made:

- There is demand from the heat pump throughout the day, however this demand is completely met by solar generation during daylight hours.
- In addition to meeting heating demand, there is sufficient solar to charge the battery. The battery is then used to meet some of the evening load, including EV charging.

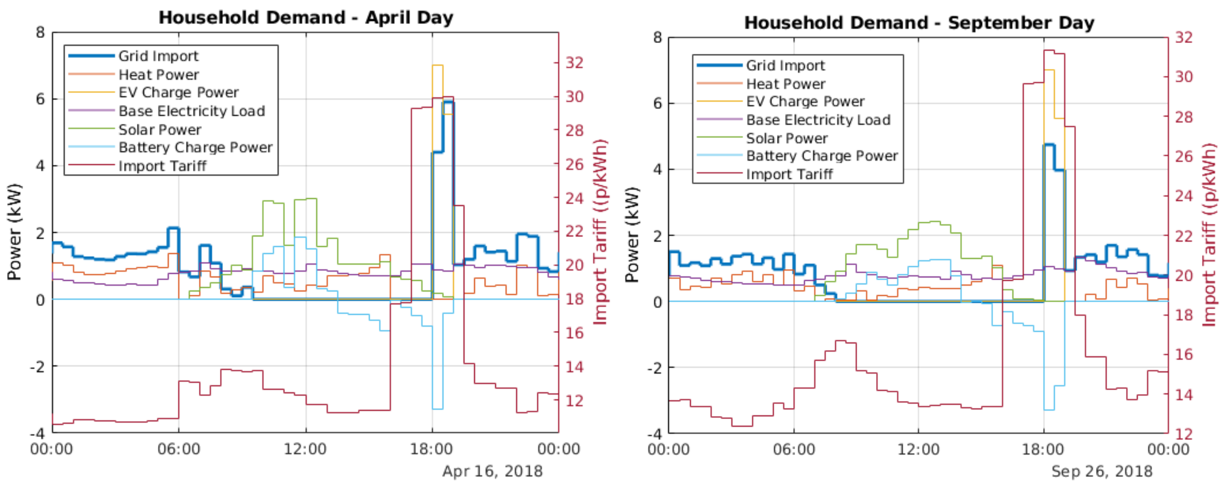


Figure 3.6 - Baseload household demand on example shoulder season days

3.2.2 Optimisation Method 1: Delayed EV Charging

The first optimisation method that has been considered is the introduction of a delay in EV charging to a time when electricity becomes cheap, i.e. there is reduced network demand. Figure 3.7 shows the modelled annual household grid import demand with this optimisation method in place, compared to the pre optimised annual household grid import demand. It can be seen that there is little change to the overall shape in demand across the year, however there is a slight increase in winter demand import peaks after this optimisation method has been implemented. Despite this, an annual estimated saving of £181 has been calculated due to shifting EV charging away from times of general peak electricity consumption.

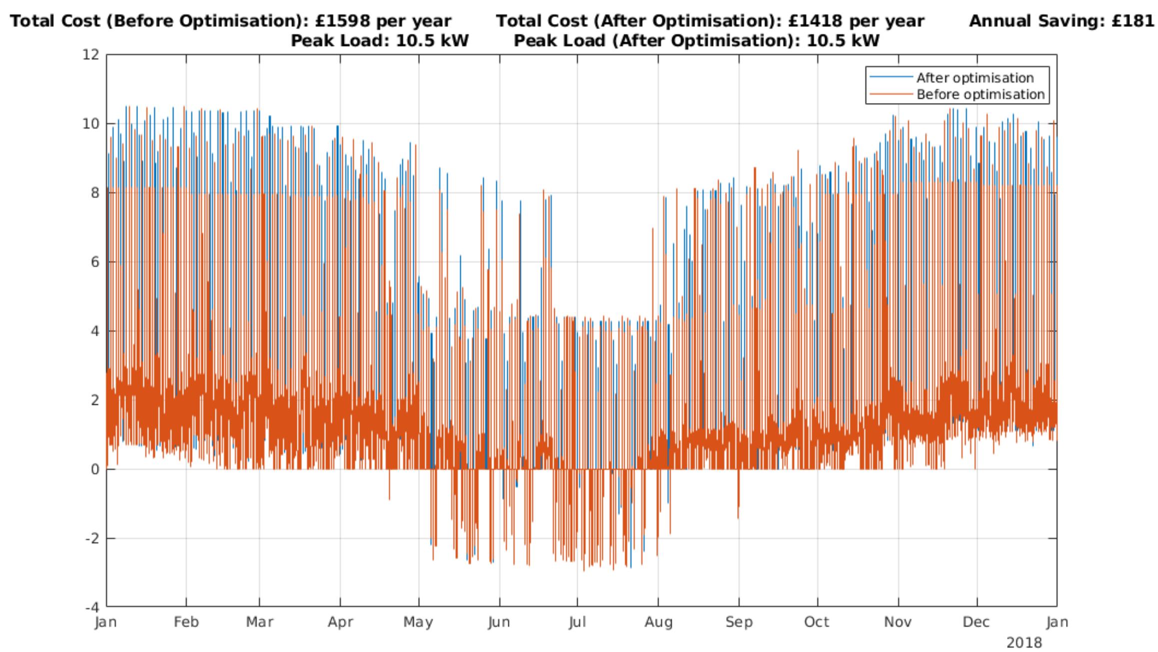


Figure 3.7 - Optimisation Method 1: Delayed EV charging grid import profile

Figure 3.8 shows the household demand on a typical winter day, when optimised with delayed EV charging. When comparing to the unoptimised case for the same day in Figure 3.4, it can be observed that the EV charging has now moved entirely away from the import tariff peak, leading to a reduction in associated import costs. However it can also be observed that, since the household heating demand was met by the boiler during the import tariff peak and outside of this peak it is met by the heat pump, shifting the EV charging outside of this time leads to the heat pump and EV charger operating simultaneously. This results in an increase in the maximum daily import power, taking it from 8kW in the pre-optimisation case to 10kW. Therefore, although this method may be effective with sparse EV uptake, moving the EV charging peak away from times where there is generally high network demand, with mass EV uptake, as is expected, this method is not likely to be sufficient in isolation at mitigating against network overload.

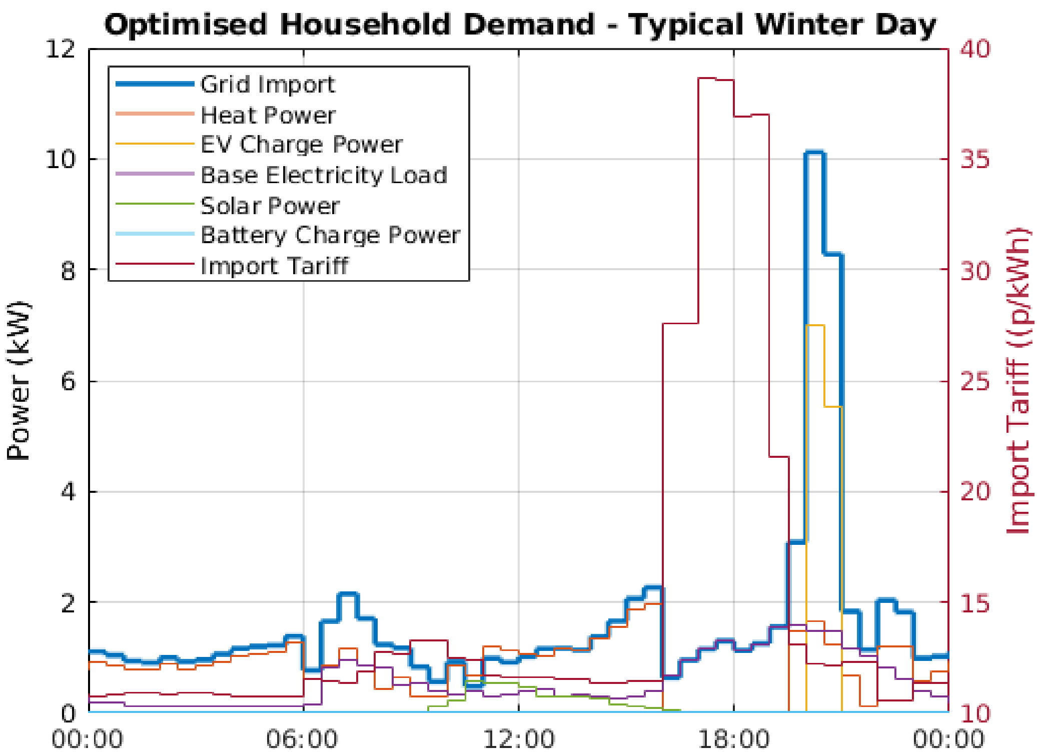


Figure 3.8 - Delayed EV charging household demand on a typical winter day (22nd January 2018)

Figure 3.9 shows the household demand on a typical summer day, when optimised with delayed EV charging. When comparing to the unoptimised case for the same day in Figure 3.5, it can be seen that there is little change to the demand profile, aside from the delay applied to the EV charging.

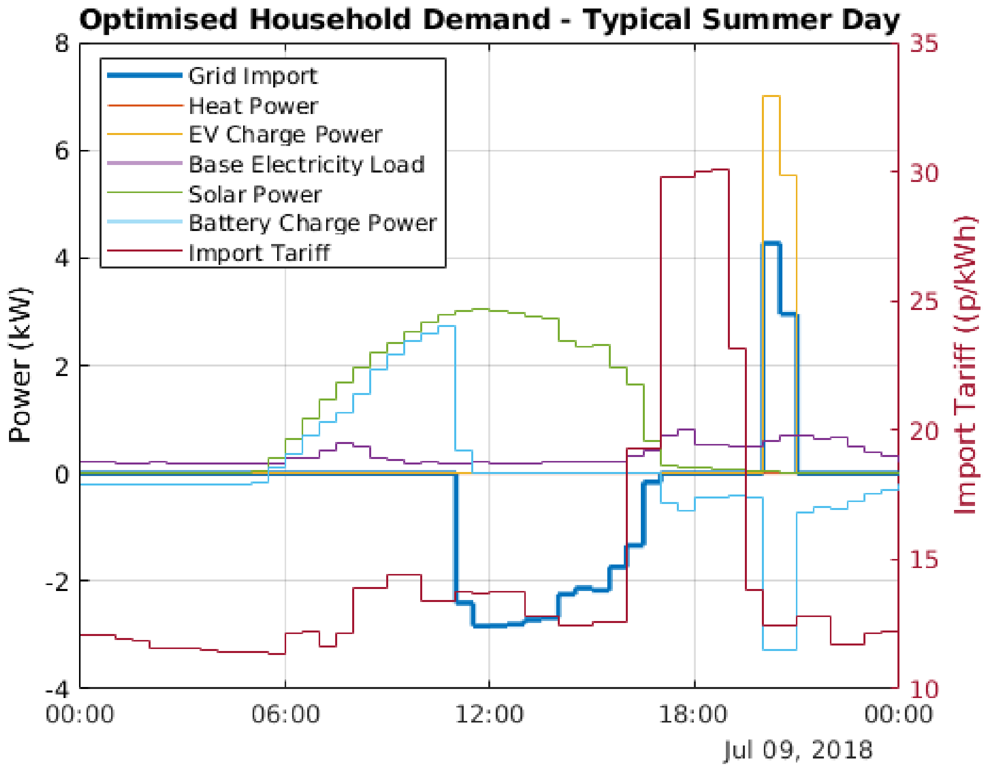


Figure 3.9 - Delayed EV charging household demand on a typical summer day (9th July 2018)

3.2.3 Optimisation Method 2: Switching From Heat Pump to Gas Boiler

An alternate optimisation method is to refrain from using the heat pump whilst EV charging is in operation, instead meeting the heating demand of the home through the use of the gas boiler. Figure 3.10 shows the modelled annual household grid import demand with this optimisation method in place, compared to the pre optimised annual household grid import demand. It can be seen that the winter demand peaks have been partially reduced through implementation of this method, whilst the overall trends throughout the year remain the same.

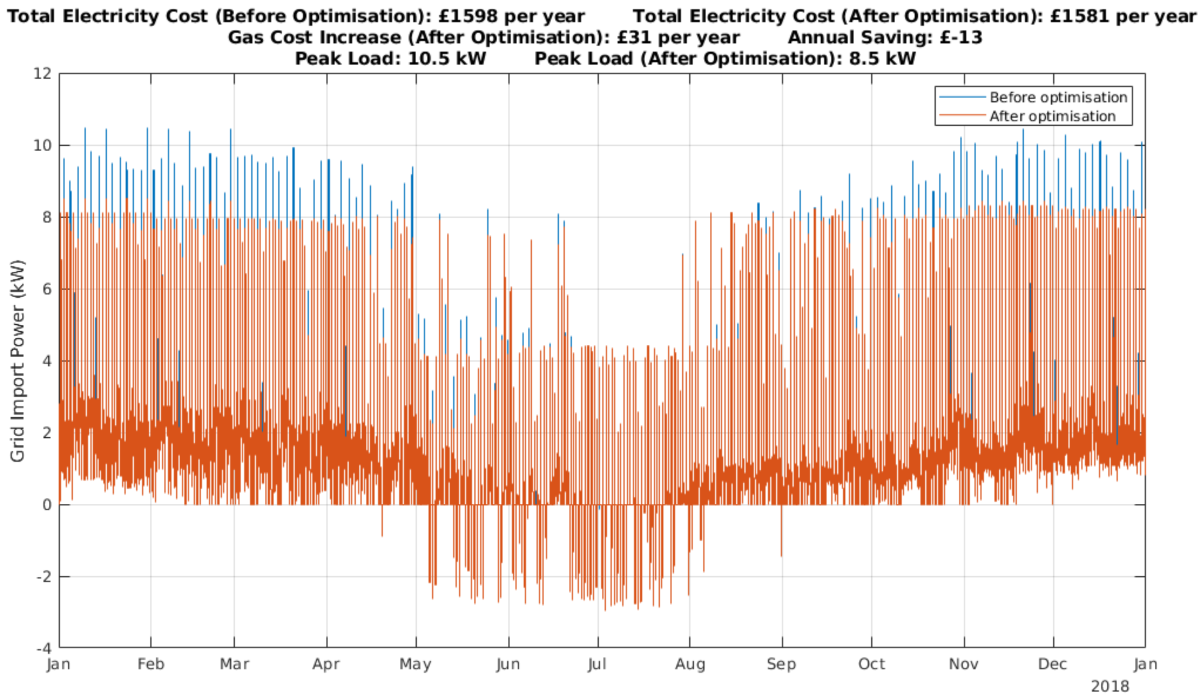


Figure 3.10 - Optimisation Method 2: Modified heat demand grid import profile

It can be seen that there is little effect on annual cost to the consumer, with an increase of £13 across the year in the optimisation case. This is potentially largely due to the fact that EV charging commonly takes place during times when the import tariff is expensive, and thus the gas boiler is used instead of the heat pump during this time anyway, coupled with the fact that EV charging is typical quite short (less than two hours) in the modelled scenario.

However, this method of optimisation could potentially be used in conjunction with Optimisation Method 1, discussed in Section 3.2.3, to enable the cost saving benefits of shifting EV charging away from times of peak import tariff, whilst preventing the increase in peak import loads observed in Figure 3.6. This coordinated control can be observed in Figure 3.11, where utilising Optimisation Method 2 alongside Optimisation Method 1 prevents the peak import load increases observed when using Optimisation Method 1 in isolation, however a notable annual cost saving is still observed.

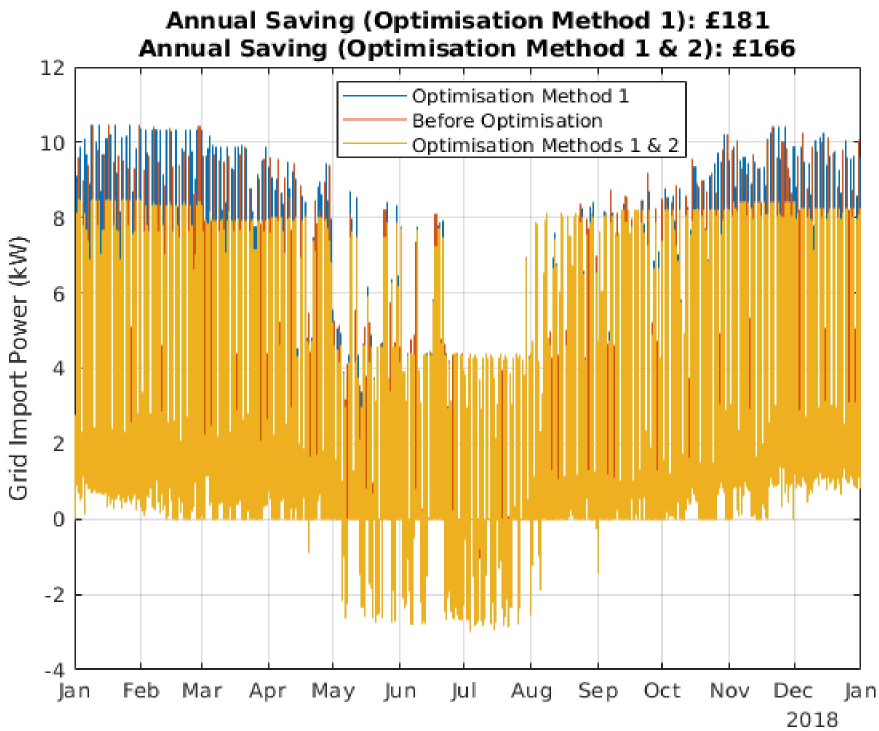


Figure 3.11 - Optimisation Methods 1 & 2: Delayed EV charging & modified heat demand grid import profile

Figure 3.12 shows the pre-optimised household demand and Figure 3.13 shows the household demand once the heat profile has been modified by meeting heat demand with the gas boiler instead of the heat pump whilst EV charging is in operation. It can see that on the 22nd January, since EV charging took place whilst electricity was expensive, the heat pump was not being used at this time and therefore there is no effect to the grid import demand on this day. On the 23rd January, prior to optimisation EV charging occured whilst the heat pump was also in operation. Thus, implementation of Optimisation Method 2 has reduced the peak demand on this day by approximately 1kW.

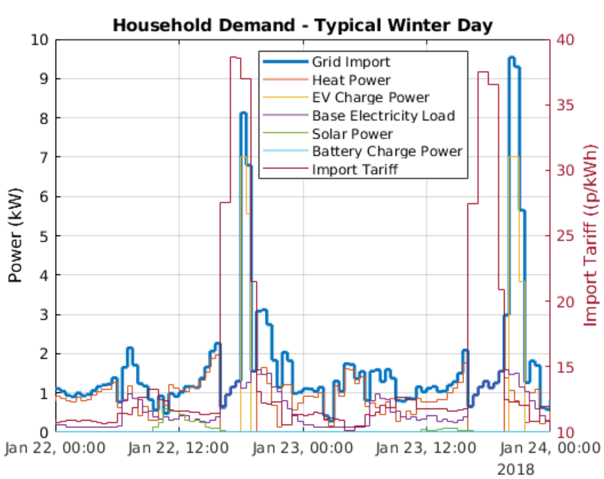


Figure 3.12 Pre-optimised household demand on a typical winter day

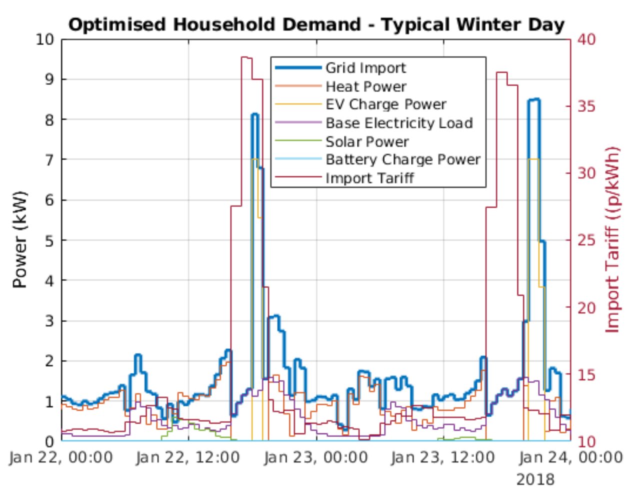


Figure 3.13 Modified heat profile household demand on a typical winter day

There was typically no change to the profile over the summer months since there was no heating demand during this time.

3.2.4 Optimisation Method 3: Constraining EV Charge Power

As discussed in Section 3.2.1, although delaying EV charging can result in notable consumer cost savings, it does little to compensate for the high load of the EV charging. A potential solution for this is to charge the EV at a reduced power. In this case, it is necessary to consider the trade off between power reduction and EV charge time increase. Consideration may also need to be given to the increase in reactive power when charging at lower power, causing a reduction in charging efficiency.

Figure 3.14 shows the annual grid import profile when EV charging has been constrained to half power (3.5kW). It can be seen that the demand peaks have been notably reduced through implementation of this method, whilst the overall trends throughout the year remain the same. This method gives a saving of £51, resulting from the increase in charging duration resulting in a proportion of the charging moving beyond the evening peak electricity import price.

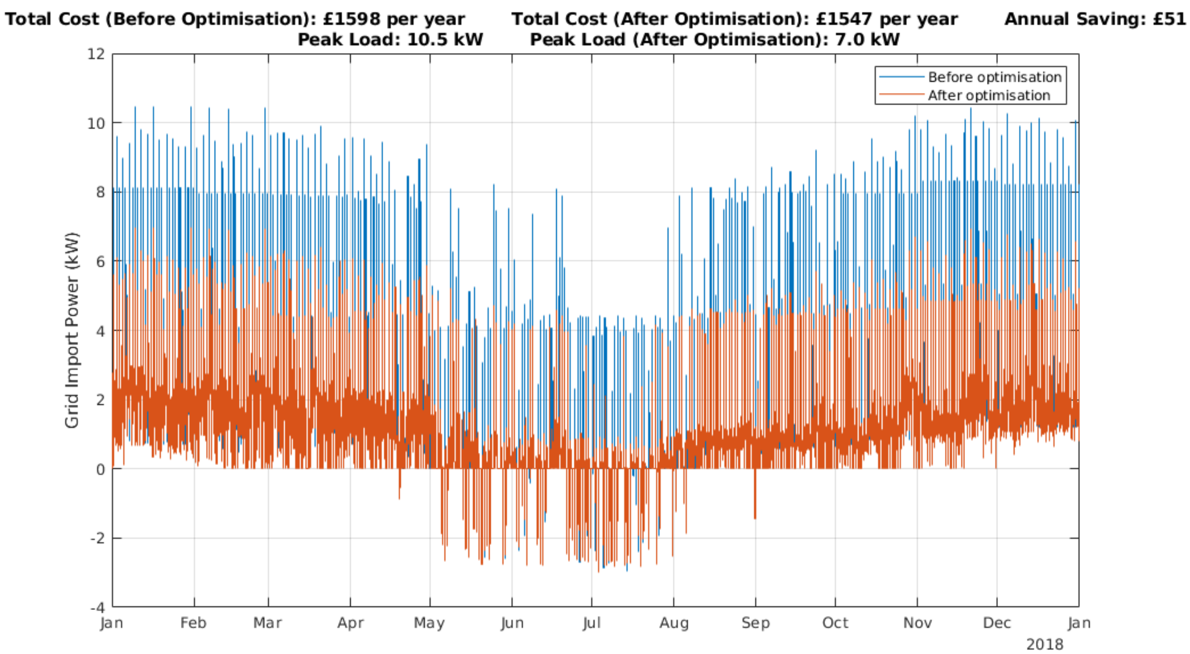


Figure 3.14 - Constrained EV charging grid import profile, with charging constrained to half power (3.5kW)

Figure 3.15 shows the household demand on a typical winter day, when optimising by halving the maximum permitted EV charge rate. It can be seen that the maximum grid import demand for this day has been reduced to around 5kW, from approximately 8kW in the unoptimised case for the same day shown in Figure 3.4. It can also be seen that the EV charge duration has increased to two hours, from one hour in the unoptimised case. Since on this particular day the EV is assumed to be connected for 14 hours, and in fact the shortest overnight connection duration across the year is 10 hours, this increase in connection duration is very unlikely to cause any issues.

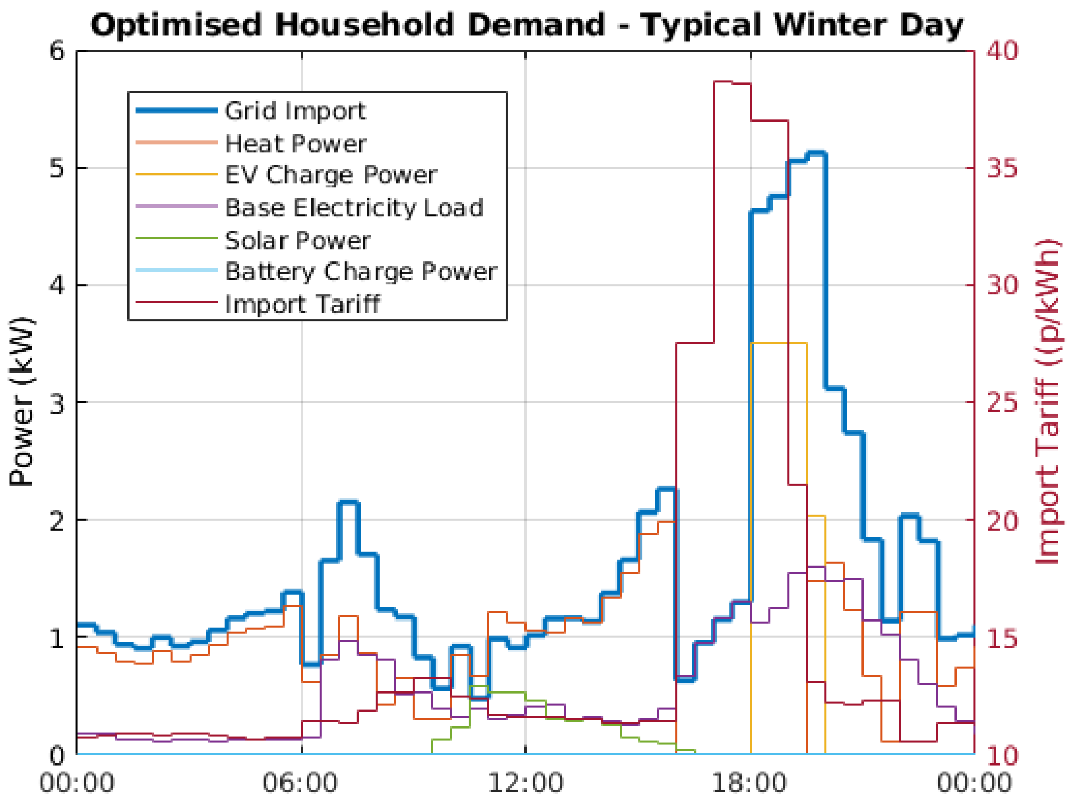


Figure 3.15 - Constrained EV charging household demand on a typical winter day (22nd January 2018)

Figure 3.16 shows the household demand on a typical summer day, when optimising by halving the maximum permitted EV charge rate. It can be seen that the maximum grid import demand for this day has been reduced to less than 1kW, from approximately 4kW in the unoptimised case for the same day shown in Figure 3.5. This is due to the EV load being reduced to much closer to the battery inverter power rating, and therefore significantly more substantial amount of the EV load is able to be met by the battery.

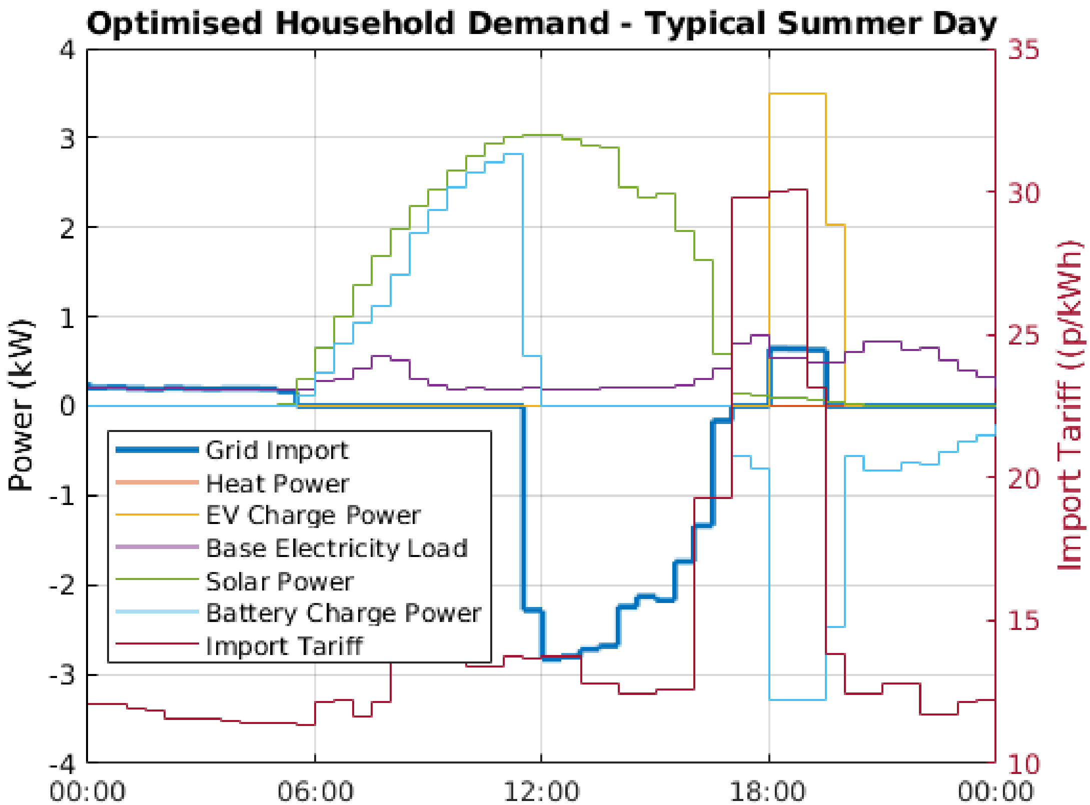


Figure 3.16 - Constrained EV charging household demand on a typical summer day (9th July 2018)

3.2.5 Summary

In summary, the modelling results above demonstrate that there is benefit, both in terms of peak demand reduction and consumer cost savings, from demand management and coordinated control of multiple energy assets. This is in line with findings from Everoze's techno-economic modelling which was also conducted at household level.

The modelling suggests that coordinated control between energy assets is necessary in order to generate optimal benefit to both peak demand reduction and consumer cost savings. For example Section 3.2.2 demonstrates that the implementation of smart EV charging, which optimises EV charging to minimise consumer cost, may actually lead to an increase in daily peak household demand. Section 3.2.3 then demonstrates that coordination between the EV charger and hybrid heating system on top of smart EV charging can maintain a large proportion of the consumer cost saving benefits, whilst mitigating the increase in peak household demand.

The modelling presented above demonstrates that potential consumer cost savings of up to nearly £200 can be achieved through implementation of simple demand management interventions. Further to this, Everoze have demonstrated that these savings can be increased in excess of £300 with a more sophisticated implementation of coordinated control, alongside additional revenue generation through DSO services.

For a DSO perspective the dominant peak demand is the sharp spike of EV charging. This means a key next step for MADE is to investigate methods where the EV charging can be both delayed from the period of peak demand and spread out over time (a combination of optimisation methods 1 and 3 above). In this scenario the coordination of assets also has a much bigger role to play as the relative power consumption levels of the EV, battery and heat pump are more comparable. This will be investigated during the MADE trial.

This modelling work has provided key insights into the diverse load profiles of each low carbon asset and how the balance changes significantly through the seasons, which will allow us to construct a meaningful field trial to explore the value of asset coordination.

4 SUPPORTING RESEARCH

A market assessment of LCTs has also been conducted by PassivSystems, in order to identify LCTs that are a good fit for use on the MADE field trials. This assessment focussed on identifying equipment which enabled third party control and could support the desired level of management, whilst maintaining high-performance.

4.1 Electric Vehicle Charging

An assessment of EV charge point providers has been carried out, in order to deduce which providers can offer the required level of interaction with their system, to facilitate demand management over the MADE trial. The main focus was placed on smart chargers, offering the required level of control over vehicle charging, with some additional consideration of vehicle-to-grid (V2G) chargers.

4.1.1 Smart Chargers

An initial desk based assessment of 41 EV charge point providers on the Electric Vehicle Homecharge Scheme[6] was performed. This assessment focused on identifying providers that offered smart charging capability, and gaining insight into those that may allow third party control of the chargepoint. The findings from this desk-based research were then summarised in a high level feature matrix.

Chargepoint providers indicated as a good potential fit for the project by the feature matrix were then contacted to discuss potential involvement in the MADE project. Following these discussions, Alfen have been identified as a strong match for use on the project, offering smart charging capabilities as well as third party control. Alfen were also involved in Electric Nation, and therefore have experience of domestic smart charging on a large scale trial.

4.1.2 Vehicle-to-grid

Since V2G is of interest for the MADE project, as well as potential future projects, an assessment of currently available V2G chargers also took place. V2G is still an emerging technology and therefore the number of consumer-ready V2G chargers available is currently very limited.

Through research into existing consumer-ready V2G chargers, the Wallbox V2G chargepoint has been selected for use on the MADE project for a number of reasons. Firstly, the charger is far more compact than other V2G chargers on the market and, in particular, its low weight allows for more flexibility in installation locations, as well as an easier installation process. The Wallbox charger is also able to sell exported energy to numerous energy suppliers, with no limitation to one particular supplier.

[6] Electric Vehicle Homecharge Scheme approved chargepoint model list - GOV.UK . [ONLINE] Available at: https://www.gov.uk/government/publications/electric-vehicle-homecharge-scheme-approved-chargepoint-model-list. [Accessed 24 April 2019].

However, V2G charging also requires EV capability. For V2G to be considered under the MADE trial, CHADEMO-equipped, V2G capable EVs are required to be used. The Nissan Leaf is an example of such an EV, and is likely to be used during the MADE trial.

4.2 Domestic Battery Market

After an assessment of available domestic battery technologies, Sonnen have been identified as a suitable provider for use on the MADE trial, due to their positive reputation alongside the availability of a suitable API. Sonnen batteries are able to operate autonomously, charging the battery with excess PV and discharging to meet household demand, whilst also having an option for a third-party to take complete control of battery charging and discharging if required. Monitoring is available and the cloud API is advantageous from an easy install point of view.

4.3 Heat Pumps

Passiv already has a strong understanding of suitable heat pump providers which could be used for the MADE field trials through extensive previous work surrounding hybrid heating systems, including the FREEDOM project. These heat pump providers include Mastertherm, Samsung and Daikin. Therefore no further research into heat pump providers was required under the MADE project.

5 CONCLUSIONS

5.1 Supporting Datasets

Previous NIA projects provide a useful data source for information on individual LCTs which may be installed within a home. In particular, the FREEDOM project has enabled PassivSystems to develop an annual forecasting tool, enabling the gas and electricity demands of a hybrid heating system to be modelled, in order to provide heat pump demand profiles for use in the MADE modelling. Through the FREEDOM project, Passiv have also gained knowledge on consumer acceptance of hybrid heating system operation, and therefore what demand management interventions may be acceptable to consumers. This will help to shape the MADE control strategy.

In addition to this, Electric Nation results demonstrate that there is scope for demand management of EV charging and that time of use incentives can be effective in influencing charging habits. The project also demonstrates that mass uptake of time of use tariffs can lead to further complications surrounding demand on the network, suggesting that coordinated control between households may be required to manage these consequences. Electric Nation has also provided insight into domestic consumer EV charging use, which has been used to develop the EV charging profiles used for the MADE modelling.

However, whilst these projects provide useful insight into the operation of LCT's in isolation, no previous projects have addressed operation of all the energy assets considered under the MADE project in combination.

5.2 MADE Modelling

The modelling presented in this report demonstrates that there is benefit, both in terms of peak demand reduction and consumer cost savings, from demand management and coordinated control of multiple energy assets. This is in line with findings from Everoze's techno-economic modelling which was also conducted at household level. It suggests that coordinated control between energy assets is necessary in order to generate optimal benefit to both peak demand reduction and consumer cost savings.

The modelling also demonstrates that potential consumer cost savings of up to nearly £200 can be achieved through implementation of simple example demand management interventions. It is expected that these example control strategies will be used in combination in the trial to unlock greater value, in conjunction with additional strategies, for example involving charging the battery when the electricity price is cheap and V2G services. In line with this, Everoze have demonstrated that there is potential for further savings exceeding £300 with a more sophisticated implementation of coordinated control.

A key output from this modelling is the observation that, from a DSO perspective, EV charging presents a sharp spike in demand, which dominates over the demand from other energy assets within the home. Thus an important next step for MADE is to investigate methods where the EV charging can be both delayed from the period of peak demand and distributed over time to reduce power, allowing for greater benefit from the coordination of assets.

Overall, this modelling work has provided key insights into the diverse load profiles of each low carbon asset and how the balance changes significantly through the seasons, which will allow us to construct a meaningful field trial to explore the value of asset coordination.

5.3 Supporting Research

A market assessment of LCTs conducted by PassivSystems, has identified LCT providers that are a good fit for use on the MADE field trials. This assessment focussed on identifying equipment which enabled third party control and could support the desired level of management, whilst maintaining high-performance.

Table 5.1 summarises the LCT providers which have been identified as a good fit for use on the MADE trial.

LCT	Identified Provider(s)	Supporting Information
EV Charge Point	Alfen	- Smart charging capabilities; - Third party control; - Experience of domestic smart charging on a large scale trial, through involvement in Electric Nation.
	Wallbox	- V2G capable; - Compact, light-weight, easy to install; - Can sell exported energy to numerous energy suppliers.
Domestic Battery	Sonnen	- Can operate autonomously, charging the battery with excess PV and discharging to meet household demand; - Option to take complete control of charge and discharge if required; - Monitoring API; - Cloud API is advantageous from an installation point of view.
Heat Pump	Mastertherm Samsung Daikin	- Identified as suitable through FREEDOM research; - Trialled on the FREEDOM project.

Table 5.1 - LCT providers which have been identified as a good fit for the MADE trial

Appendix 1 - Electric Nation Data Validation

A1.1 Introduction

The Electric Nation data set has been validated against EV charging data published by the Office for Low Emission Vehicles (OLEV)[7]. This OLEV data set contains close to 3.2 million charging transactions recorded across approximately 25,000 OLEV funded domestic charge points.

Alongside the Electric Nation data analysis presented in Section 2.1.2, the data was also reviewed to ensure that there was consistency between the two demand control providers and across the various trials, and to determine whether it was appropriate to analyse the data set as a whole for the purposes of the MADE project.

A1.2 Validation Against OLEV Data

The OLEV data set contained the following information for each transaction:

- Time of connection
- Time of disconnection
- Energy consumed

No information on vehicle capacity or nominal charge rate was included, therefore estimated charge duration and state of charge increase cannot be calculated. Hence, the following parameters have been compared between the Electric Nation and OLEV data sets:

- Connection duration (See Section A1.2.1)
- Time of connection (See Section A1.2.2)
- Energy consumed (See Section A1.2.3)

A1.2.1 Connection Duration

It can be seen from Figure A1.1 that the connection duration distributions for the Electric Nation and OLEV data sets are comparable, with both data sets observing a peak between thirty minutes to four hours and between nine and sixteen hours. The OLEV data has a slightly higher peak than the Electric Nation data at thirty minutes to four hours, where as the Electric Nation data has a slightly higher peak at nine to sixteen hours. As a result, the OLEV data has a slightly lower mean connection duration than the Electric Nation data, however the difference is only approximately 30 minutes.

[7] Electric Chargepoint Analysis 2017: Domestics - GOV.UK . [ONLINE] Available at: https://www.gov.uk/government/statistics/electric-chargepoint-analysis-2017-domestics. [Accessed 22 May 2019].

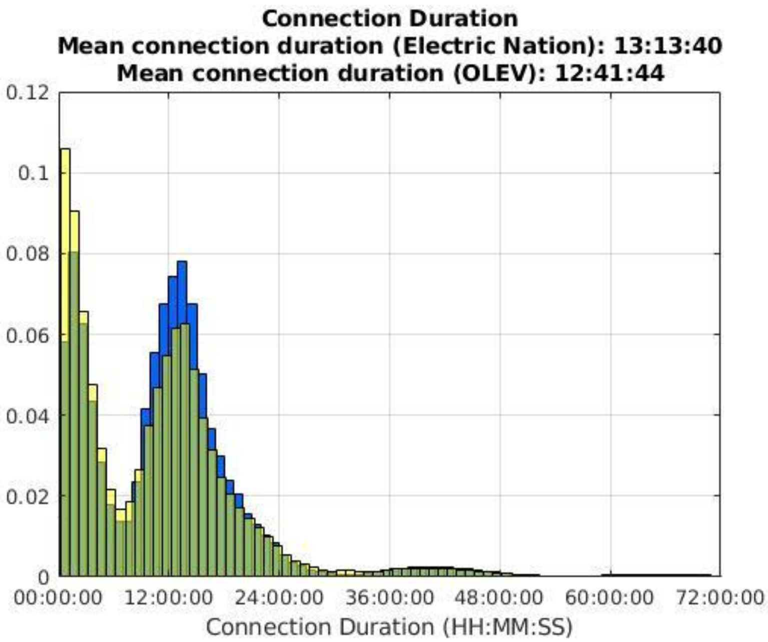


Figure A1.1 - Connection duration distribution comparison for Electric Nation and OLEV data sets

A1.2.2 Time of Connection

It can be seen from Figure A1.2 that the time of connection distributions for the Electric Nation and OLEV data sets are comparable, with both data sets observing an evening peak. Based on the Electric Nation data, time of connection was most commonly between 17:00 and 19:30. Based on the OLEV data, time of connection was most commonly between 17:00 and 19:00. The mean time of connection was approximately one hour earlier for the OLEV data.

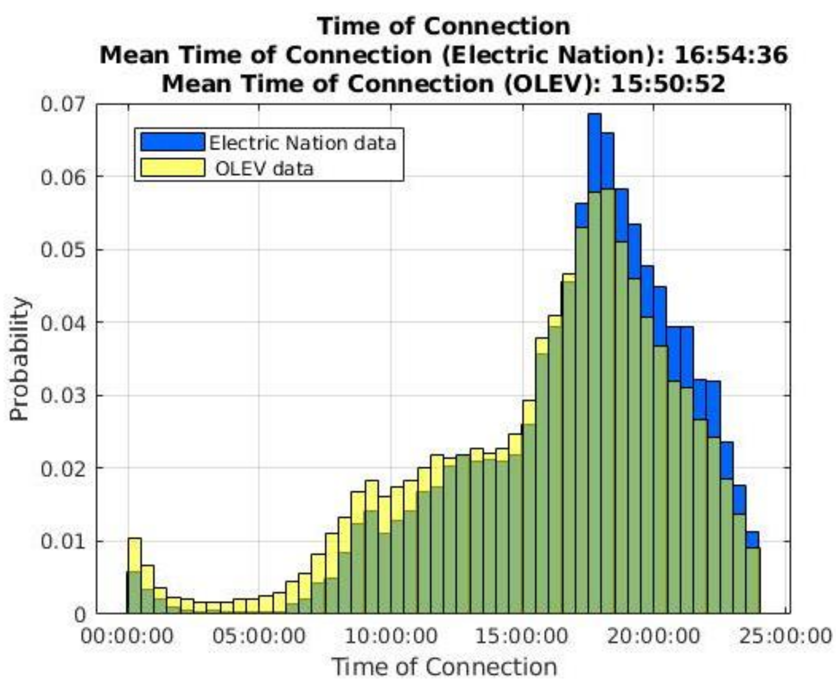


Figure A1.2 - Time of Connection distribution comparison for Electric Nation and OLEV data sets

A1.2.3 Energy Consumed

It can be seen from Figure A1.3 that the energy consumed distributions are comparable for the Electric Nation and OLEV data sets, with energy consumed most commonly between one and ten kilowatt-hours for both.

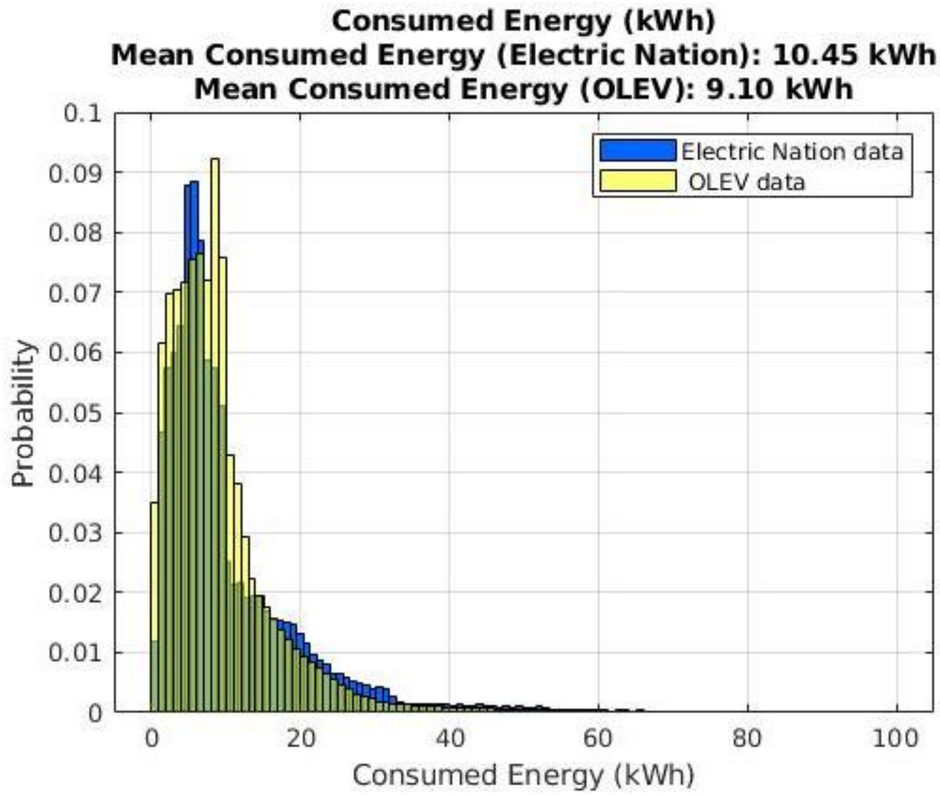


Figure A1.3 - Energy consumption distribution comparison for Electric Nation and OLEV data sets

A1.3 Electric Nation Data Consistency

In order to ensure that there was adequate consistency within the Electric Nation data set, the charging transactions provided were separated into the two demand control providers; GreenFlux and CrowdCharge. Charging transactions were then further separated by trial number; Trial 1, Trial 2, Trial 3, or those not linked to a trial. These eight distinct groups (see Table A1.1) were then contrasted to determine whether each data set was comparable.

Electric Nation Data Comparison Groups			
GreenFlux Trial 1	GreenFlux Trial 2	GreenFlux Trial 3	GreenFlux Not linked to trial
CrowdCharge Trial 1	CrowdCharge Trial 2	CrowdCharge Trial 3	CrowdCharge Not linked to trial

Table A1.1 - Groups compared to ensure consistency between Electric Nation demand control providers and trials

In line with the analysis presented in Section 2.1.2, comparison focused on the following:

- Connection duration (*See Section A1.3.1*)
- Charge duration (*See Section A1.3.2*)
- Time of connection (*See Section A1.3.3*)
- Vehicle state of charge (*See Section A1.3.4*)

A1.3.1 Connection Duration

Figure A1.4 shows the distribution of connection durations for the eight distinct groups shown in Table A1.1. It can be seen from this figure that the connection duration distribution is comparable between all groups.

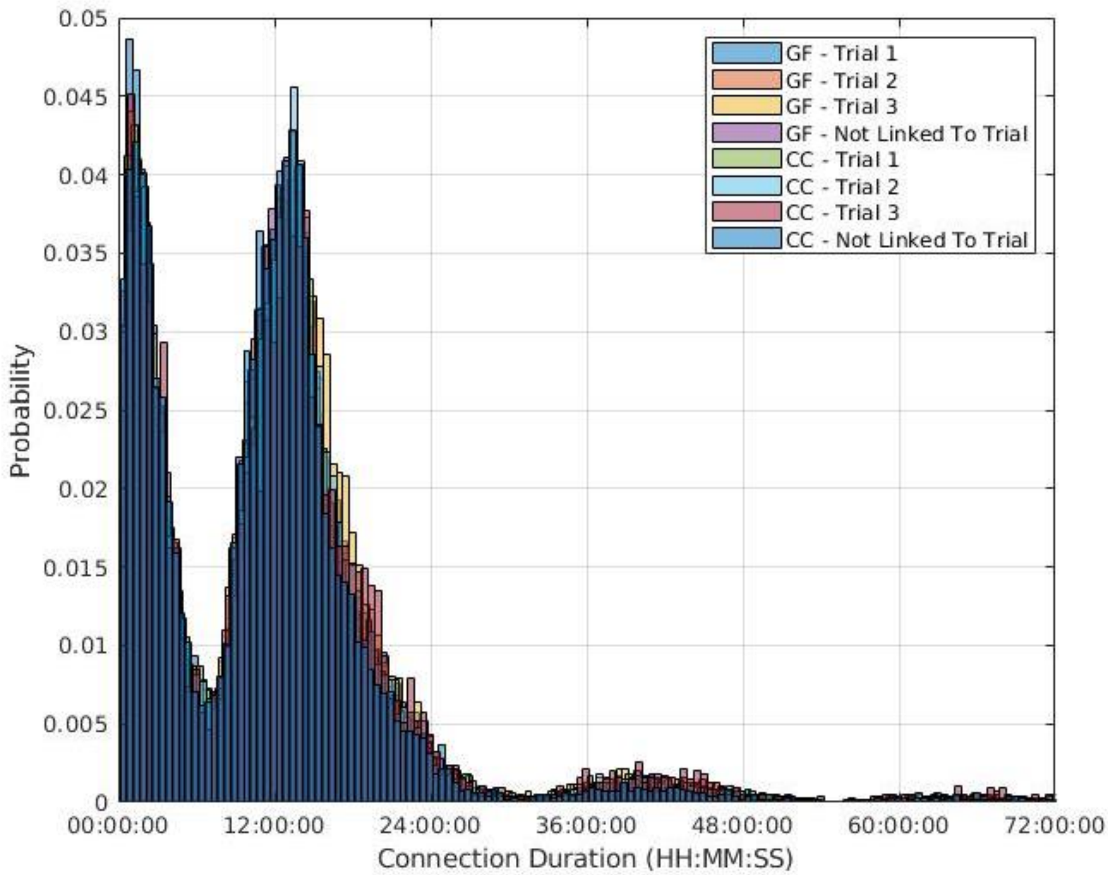


Figure A1.4 - Distribution of connection durations categorised by demand control provider and trial number

Additionally, Table A1.2 displays the mean connection duration for each of the considered groups. Again, these are comparable between groups.

	Trial 1	Trial 2	Trial 3	Not linked to a Trial	Total
GreenFlux	13:26:55	13:02:29	13:51:48	14:18:47	13:41:18
CrowdCharge	12:53:15	13:03:30	13:24:13	11:46:26	12:38:34
Total	13:08:54	13:02:52	13:41:41	13:16:51	**13:13:40**

Table A1.2 - Mean connection duration categorised by demand control provider and trial number

In summary, it is deemed acceptable to draw conclusions regarding connection duration from the data set as a whole.

A1.3.2 Charging Duration

Figure A1.5 shows the distribution of estimated charge durations for the eight distinct groups shown in Table A1.1. It can be seen from this figure that the estimated charge duration distribution is comparable between all groups.

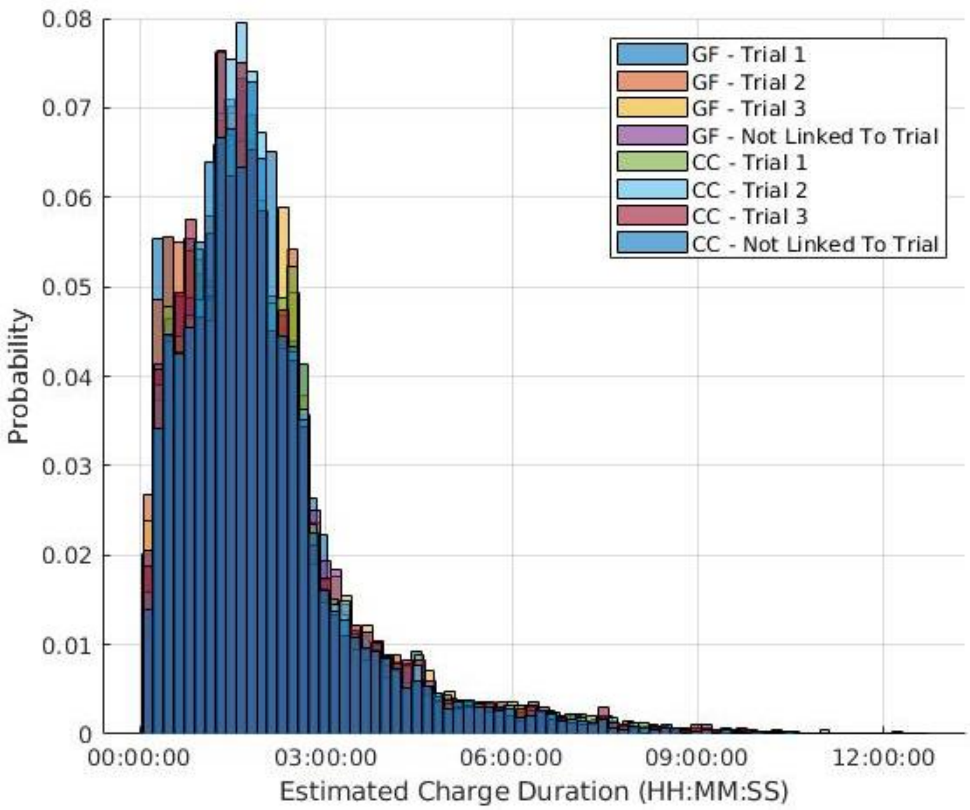


Figure A1.5 - Distribution of estimated charge durations categorised by demand control provider and trial number

Additionally, Table A1.3 displays the mean estimated charge duration for each of the considered groups. Again, these are comparable between groups.

	Trial 1	Trial 2	Trial 3	Not linked to a Trial	Total
GreenFlux	01:54:59	01:49:04	02:02:04	02:00:14	01:56:08
CrowdCharge	02:00:40	01:57:27	01:59:24	01:57:36	01:59:02
Total	01:58:01	01:52:15	02:01:05	01:59:09	**01:57:25**

Table A1.3 - Mean estimated charge duration categorised by demand control provider and trial number

In summary, it is deemed acceptable to draw conclusions regarding charge duration from the data set as a whole.

A1.3.3 Time of Connection

Figure A1.6 shows the distribution of time of connection for the eight distinct groups shown in Table A1.1. It can be seen from this figure that the time of connection distribution is comparable between all groups.

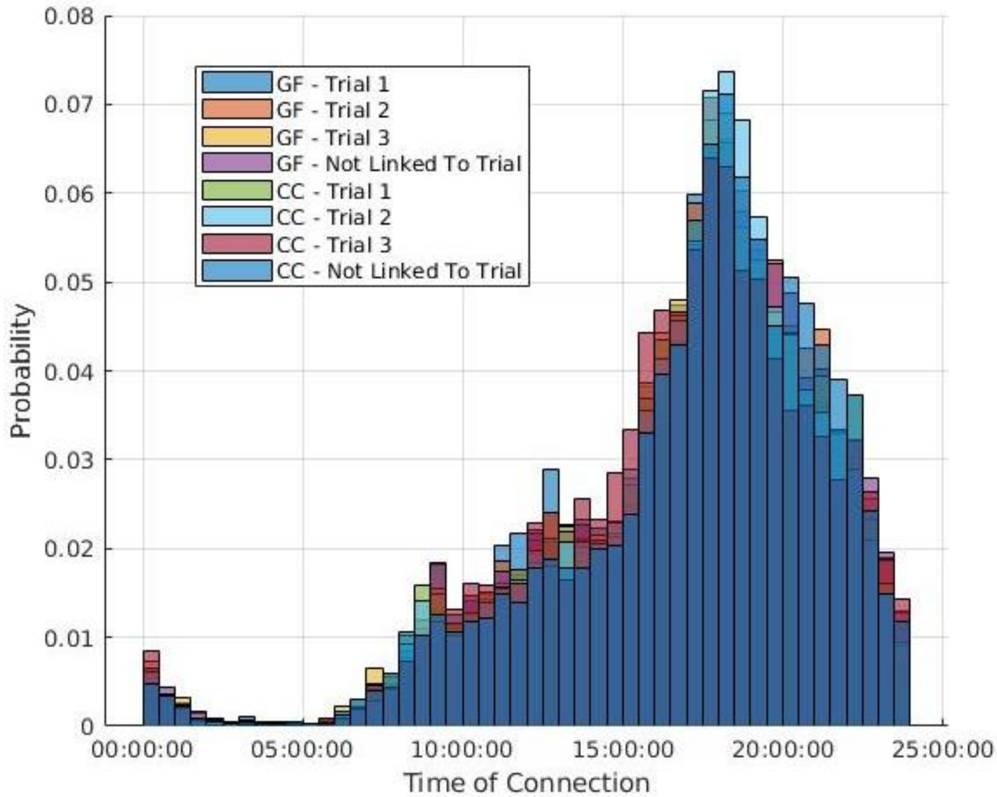


Figure A1.6 - Distribution of time of connection categorised by demand control provider and trial number

Additionally, Table A1.4 displays the mean time of connection for each of the considered groups. Again, these are comparable between groups.

	Trial 1	Trial 2	Trial 3	Not linked to a Trial	Total
GreenFlux	16:38:49	17:01:45	16:49:44	16:58:08	16:52:25
CrowdCharge	16:53:00	16:55:17	16:41:49	17:09:53	16:57:21
Total	16:46:24	16:59:18	16:46:50	17:02:55	**16:54:36**

Table A1.4 - Mean time of connection categorised by demand control provider and trial number

In summary, it is deemed acceptable to draw conclusions regarding time of connection from the data set as a whole.

A1.3.4 Vehicle State of Charge (SOC)

Figure A1.7 shows the distribution of vehicle state of charge increase for the eight distinct groups shown in Table A1.1. It can be seen from this figure that the state of charge increase distribution is comparable between all groups.

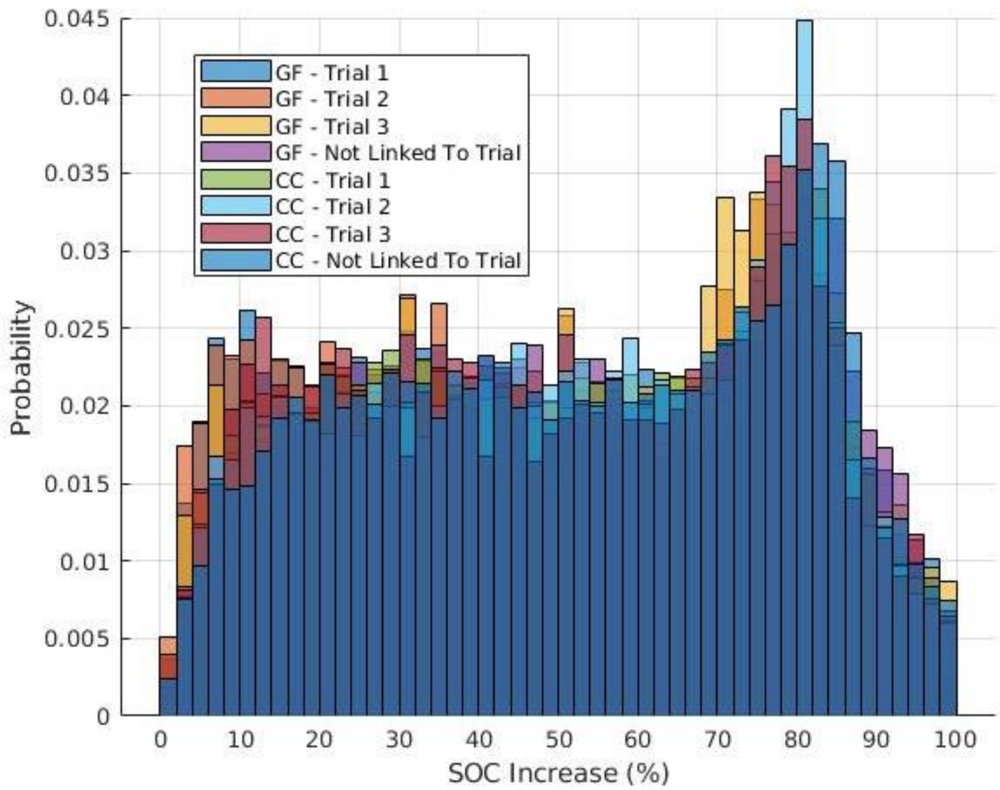


Figure A1.7 - Distribution of vehicle state of charge increase categorised by demand control provider and trial number

Additionally, Table A1.5 displays the mean state of charge increase for each of the considered groups. Again, these are comparable between groups.

	Trial 1	Trial 2	Trial 3	Not linked to a Trial	Total
GreenFlux	48.5	47.2	51.7	51.4	49.6
CrowdCharge	51.3	51.9	50.7	52.8	51.8
Total	50.0	49.0	51.3	52.0	**50.5**

Table A1.5 - Mean SOC increase categorised by demand control provider and trial number

In summary, it is deemed acceptable to draw conclusions regarding state of charge increase from the data set as a whole.

A1.4 Summary

The results presented in Section A1.2 suggest that the Electric Nation charging data is comparable to the EV charging data provided by OLEV. This provides confidence that the Electric Nation data is reflective of typical EV charging habits, and is suitable for use in the MADE project modelling.

The results presented in Section A1.3 suggest that there is consistency in the parameters of interest across both demand control providers and over all trials. In summary, for the purposes of the analysis conducted as part of the MADE project, it is deemed acceptable to consider the data set in its entirety.