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Matriculation number s1425486

BEng Hons Individual Project

Smart EV Charging and Demand Response: Is it really that complicated?

April 25, 2018

Mission Statement

Description and Objectives of the Project

The aim of the project is to analyse the feasibility of implementing a remote on-off switching control scheme of charging a fleet of "high-end" electric vehicles (HE-EVs, which are generally defined as EVs with battery capacity of around 100 kWh, or higher). The work on the project will have several stages:

- Initial analysis will provide a detailed review of existing grid-to-vehicle (G2V) and vehicle-to-grid (V2G) demand response methods.

- Afterwards, a machine learning analysis of a representative set of HE-EV user profiles will be performed, in order to predict the time-varying (i.e. time of the day, day of the week) charge status and potential of individual vehicles in the HEEV fleet to contribute to the target control objectives.

- Next stage will be dedicated to a design of a flexible and computationally efficient algorithm to calculate the predicted demand-response capabilities of a sample HE-EV fleet.

- The final stage will be related to the techno-economic analysis of developed control schemes and algorithms, using sample data provided by the industrial supervising company (Jaguar Land Rover, JLR).

Motivation and Relevance

This project will examine the techno-economic feasibility and initial design of a control scheme that would allow Jaguar Land Rover (JLR) to aggregate demand response across a fleet of their HE-EVs. By aggregating the demand response of a fleet of HE-EVs charging on the same grid JLR will be able to bid on the energy market by offering grid balancing/support services and receive the corresponding compensation for the service. Through the incentivising of customers to opt in to the scheme and remuneration for provided demand response functionalities (e.g. by offering remuneration to be used towards vehicle servicing for HE-EV owners), this demand-response control scheme could generate an additional income for the company on a product that has already been sold. An important constraint is that the implementation of the scheme should result in the minimum, or no discomfort for the HE-EV users, as the on-off switching of the chargers will not impact user-required state of charge of HE-EV battery and time at which it should be delivered.

Project Scope

This project will focus on controlling only HE-EVs charged at a home charging station, with simple on-off remote control switching and without any further "smart control functionalities" (e.g. control of charging power level, or electricity tariff-based charging control). The demand response capabilities of the modelled HE-EVs will be analysed in both the English and Scottish low voltage grids (220V) . Any data and information not provided by the JLR will be based on available public specifications of similar HE-EVs, e.g. a Tesla Model S 100D.

The academic supervisor and student are satisfied that this project is suitable for performance and assessment in accordance with the guidelines of the course documentation.

Approved: ____

Michael McDonald, Student

Approved: ____

Dr Sasa Djokic, Supervisor

Energy Systems Research Institute

Abstract

Electricity grids are facing challenges globally due to rising consumption and an increasing share of renewable generation. This combined with rapid growth in the sales of EVs poses a problem to the ageing power transmission network in the UK. Using bidirectional chargers, it is possible to provide support services to the network in the form of aggregated V2G capable EV fleets. Using a simple combinational algorithm that charges half the fleet on arrival and the other half as late as possible it was proven that the same services can be offered using a larger fleet and unidirectional chargers. To provide the same level of service the fleet needs to be 3.9 times greater for demand turn down, or the exact same size for demand turn up services. This virtual power plant, of remotely activated vehicles, offers a solution to the expected issues on the grid without the need for expensive bidirectional chargers. This sheds light on the over complication of most research that uses complex bidirectional systems instead of the simpler unidirectional ones capable of producing the same result and opening an additional revenue stream to OEMs, EV owners and DSR aggregators.

Index Terms: EV (Electric Vehicle), Vehicle to Grid (V2G), Demand Side Response (DSR), Original Equipment Manufacturer (OEM)

Statement of Achievement

As an individual I developed the idea of using unidirectional vehicles for demand response during my internship at JLR. Following discussions with my line manager, Abhishek Sampat, I proposed the project as my final year honours Dr Sasa Djokic who agreed to supervise it.

Upon the project being accepted, I carried out further research into whether this style of system had been used in previous literature and completed an in depth analysis of all current demand response technologies and service contracts offered by National Grid. Due to encountering issues regarding their obligation to protect and not distribute data collected, JLR were unable to provide any form of location or behavioural data to be used to train a machine learning algorithm. I then collected several samples of location only data from colleagues to try and build my own EV simulation but time limits of the project meant that this was not a feasible proposal. This data that was collected did however allow for simple processing to be done but the sample was not sufficient to develop a user profile with accurate representation of the population demographics.

Following the research and initial testing stage I developed from scratch a Matlab algorithm that simulated the arrival and departure times of a fleet of EVs. This simulated fleet allowed me to develop the charging algorithm that scheduled all the vehicles and acted on a demand response signal to change the current output power. The midpoint algorithm was developed as a stepping stone during a supervisor meeting having already shown the results for the ASAP and ALAP algorithms. This was a logical progression in the thought of both parties, as such the concept is the combined intellectual contribution of both parties but work was completed my myself.

Following the initial testing of the algorithms I developed the first sensitivity analysis under request by my supervisor. The second and third sensitivities were my ideas and my work. The last section of research was the comparison to V2G capable chargers that I was urged to do by my supervisor but completed on my own. thereafter the only work to complete was a report write up and presentation of results in which I had significant guidance on the style of writing and formatting techniques.

Declaration of Originality

I declare that this honours project is my original work except where stated.

Signed: ____________________________________

Michael McDonald, S1425486

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List of Figures

Nomenclature

The following symbols will be used within the body of the document and are defined as below

N Size of Fleet

P_{Arrive} Probability of vehicle Arriving

P_{AtHome} Probability of vehicle present at home

P_{Depart} Probability of vehicle Departing

ALAP As Late As Possible scheduling algorithm

ASAP As Soon As Possible scheduling algorithm

BEV Battery Electric Vehicle

DSR Demand Side Response

EV Electric Vehicle

Ideal Theoretical best case scheduling algorithm

MidP Combined ASAP and ALAP scheduling algorithm

PHEV Plug in Hybrid Electric Vehicle

SoC Vehicle State of Charge (%)

1 Introduction

Global warming has in recent years become a serious concern to many citizens and governments around the world, with 16 of the 17 warmest years on record occurring since 2001 [10].In The UK, the transport sector is the largest representing 40% of the total energy consumption in 2016. Of this, 65% of was consumed by domestic transport [2]. With this sector's consumption growing for the third consecutive year by 1.9 percent from 2015 to 2016, it is no wonder that regulatory bodies around the world are combining to target internal combustion vehicles as a significant contributor of global warming. In response to the United Nations Paris Agreement of 2015[1], the UK government has produced legislation and is continuing to subsidise the move away from fossil fuel powered transport and electricity generation in an effort to promote the growth of renewable generation and use of electric and hybrid-electric vehicles within the UK.

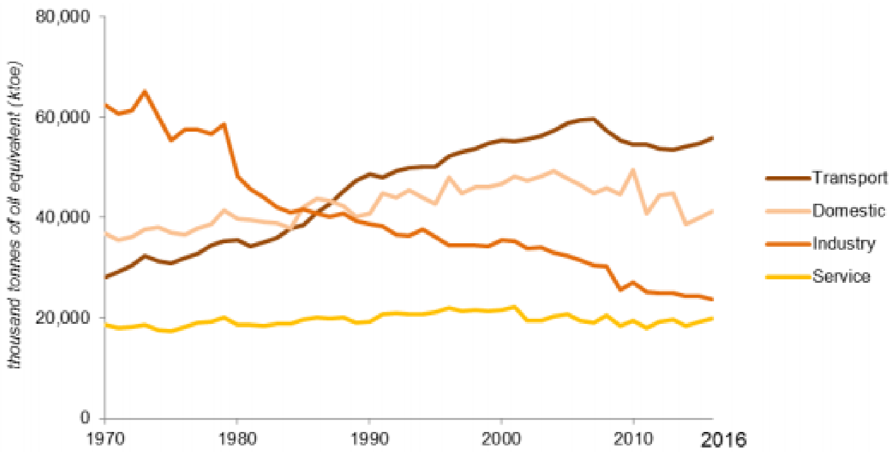


Figure 1.1: UK Annual Energy Consumption by Sector [2].

The growing number of electric vehicles on the roads that require charging is one of the multitude of factors contributing to the growing global electricity demand that more than doubled between 1990 and 2016 [3] and in particularly the growth of the transport sector in the UK, Figure 1.1. This increasing demand is being met with a larger share of renewable generation due to the extensive investment into renewable generation to control emissions, Figure 1.2. Renewable energy generation is currently largely dependant on weather variations and as such is significantly more volatile than conventional fossil fuel based generation plants. In addition to being more volatile, thanks to targeted subsidies home-owners have been encouraged to install solar panels on their homes and are providing distributed generation. Distributed generation is harder to control and manage as the number of users increases with non radial power flows able to raise the end node voltage beyond the normal operating limits [11].

[1]The Paris Agreement builds upon the Convention and for the first time brings all nations into a common cause to undertake ambitious efforts to combat climate change and adapt to its effects, with enhanced support to assist developing countries to do so. As such, it charts a new course in the global climate effort.

These trends in generation and demand are expected to be extremely testing on the grid with major upgrades to infrastructure needed if no alternative solutions are found. One solution being explored is the introduction of smart meters, offered to all homes and small businesses by 2020 [12]. With smart metering in place, National Grid will be able to incentivise users to reduce or increase demand at times of strained generation. This is predicted to alleviate some of the issues but is not expected to be a complete solution. Another option showing significant market growth in recent years has been the ancillary services market.

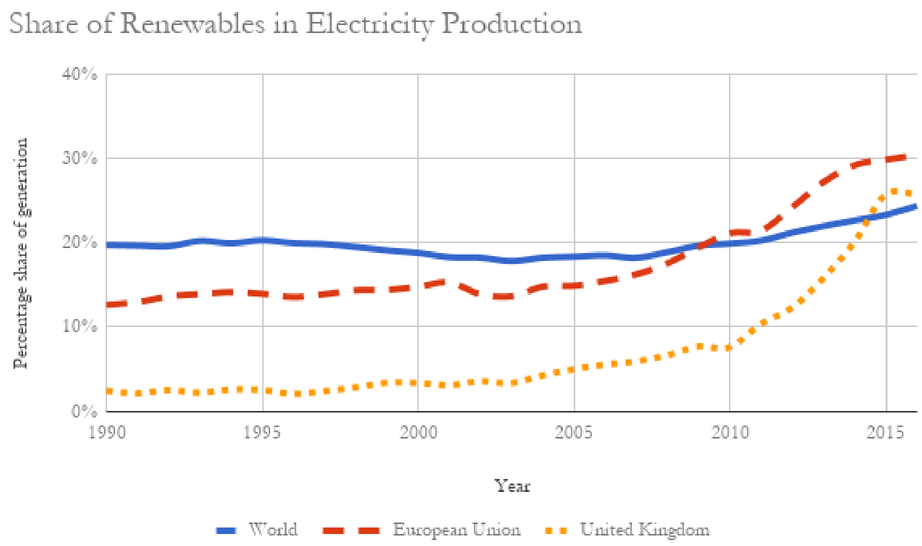


Figure 1.2: Share of Renewable Electricity Generation in electricity production [3].

When the grid demand and supply are mismatched, due to a change in demand or fault in generation, the system operators work are required to balance this difference to maintain the frequency within 1% of 50Hz. To balance a mismatch in generation faster than the response time of a typical thermal generator, the system operators contract providers of fast turn on turn off generation to be readily available if required. These contracted arrangements allow the system operators to balance the supply of power to the grid without high frequency fluctuations to the main generation plants and maintain the equilibrium throughout the day. The contracted fast reaction power service contractors are expected to turn up or down generation within a pre-defined time to provide a change in power for a specific duration until the larger generation facilities catch up or the demand changes again.

The rise of electric vehicles (EVs) has been accompanied by significant amounts of research into the power electronic charging and the use of bidirectional converters. This provides the ability for an electric vehicle to serve as a distributed energy storage systems capable of providing grid services and so instead of providing a problematic load could offer a solution to the increased volatility in supply. Bidirectional converters allow a flow of power from Vehicle to Grid (V2G) and with the first chargers of this type available to consumers in the summer of 2018 their effectiveness soon to be proven [13].

V2G projects over the years have received considerable attention and funding. £30 Million was invested in V2G technology through the Innovate UK scheme to "*unlock the potential for electric vehicles to help power people's homes*"[14]. This technology has been in the trial stages of academia for quite some time and although it is now deemed as commercially viable by the likes of Ovo Energy, it still has pitfalls. One such pitfall is the additional cost of the bidirectional power electronics and so if it is possible to provide similar grid services without the additional cost then it may be more easily accepted by early adopters.

This project will explore the potential of EVs to be used for grid services by controlling their times of charging and rates of power required through grid-to-vehicle applications (G2V). The aim was to provide a basic control algorithm that allows a fleet of unidirectional vehicles to provide the same demand response services as one supplied with V2G chargers. With extensive work already done by [9], [5], [15], [16], [17] and [18] in designing V2G grid service systems; this project will explore the possibility of modifying these to use unidirectional chargers only. Such a system could allow EVs to be aggregated as a part of the DSR service irrespective of their charge point capabilities. The control and "smart" portion of the system would be a cloud controlled platform that can be scaled in line with demand for EVs and is not restricted by expensive hardware installations.

2 Literature Review

Using EVs for grid services through V2G is a concept that has been explored by an fast growing number of sources with over 1000 papers published in IEEE Explore containing the acronym in their titles. This service has the potential to provide a large amount of support to the grid and yet has only reached commercially available projects in the Q1 of 2018. In the digital age where cars come preconfigured with LTE connections and cloud integrated machine learning schedules, it makes sense to explore the potential of using cheaper (non-smart) chargers and a smart car to achieve the same results. To fully understand the market and grid services that are applicable to this kind of cloud based scheduling service research has been conducted into the market size and growth of electric vehicles and the services offered by the grid system operators in the United Kingdom. This research will have a predominant focus on UK based statistics due to the support from a UK automotive OEM throughout the project.

2.1 Electric Vehicles and the Power Grid

EVs have historically been expensive vehicles with limited ranges and long charge times; as such they have struggled to gain traction in a petrol and diesel internal combustion engine (ICE) dominated market. Through extensive investment into battery technology and the aid of recent legislation[2] there have been rapid developments in driving range and prices of EVs leading to an almost exponential growth in electric vehicle sales. This growth will further promote reductions in cost and improvement in range. These advancements have been and will continue impacting the primary choice of new vehicle for many people from an internal combustion engine (ICE) to an electrified alternative of either plug in hybrid (PHEV) or battery electric vehicles (BEV). The numbers of EVs sold in Europe has now reached 1 Million and the trend is expected to continue to grow steadily, Figure 2.1. The exact outcome that the predicted number of electric vehicles will have on the grid is uncertain with significant difficulties being found in modelling the load that an electric vehicle represents [19].

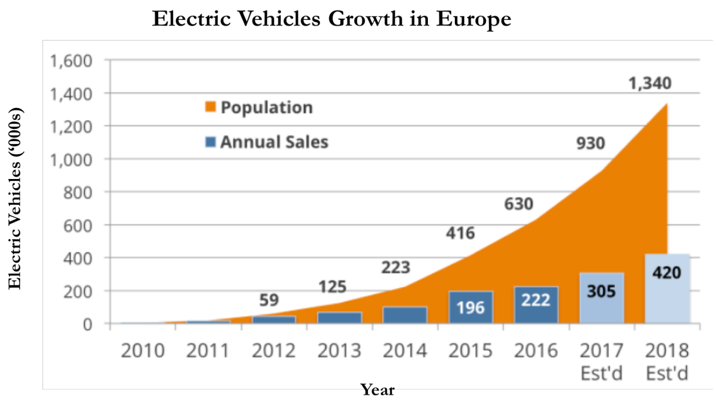


Figure 2.1: EV Growth in Europe [4].

[2] The UK government has proposed a ban on the sale of all petrol and diesel cars by 2040

Certain high end electric vehicles are capable of rapidly charging at over 200kW with the correct infrastructure. This is not possible with home chargers due to the power ratings on domestic transmission and so without additional upgrades the maximum home charge rate is 7kW. While EV uptake is still minimal it is difficult to predict the exact effects that these additional loads will have on the low voltage and wider medium and high voltage networks in terms of end node voltage and demand profiles.

Table 2.1: Manufacturer specifications for sample vehicle classes (2018 models).

Class	Sample Vehicle	Battery Capacity	Range (miles)	Max Charge Rate
PHEV Small	Toyota Prius	8.8kWh	25	3.6kW
PHEV Large	Audi Q7 e-Tron	13.7kWh	37	7kW
BEV small	Nissan Leaf	40 kWh	165	50kW
BEV large	Jaguar I-Pace	90 kWh	300	150kW
BEV luxury	Tesla Roadster 2	150 kWh	620	200kW

2.1.1 Effects on Low Voltage network

Most previous work as done by [15], [20] and [21] have examined EV penetration and the adverse effects or lack thereof that these will have on large-scale electric power systems. Although the transmission network is required to balance for low voltage networks to receive power an often-overlooked aspect is that of whether EVs will have an adverse effect on the low voltage distribution network and in particular on the per unit voltages received at houses and the power throughput of distribution transformers. One such study done by [22] shows that through load monitoring, the maximum transformer load for three houses can be maintained below the rated 25kW at any time without any adverse effects noticed by the consumers.

Electric vehicles models in the simplest terms can consist of a converter and battery pack and would not be that difficult to model accurately. The difficulty in modelling occurs when, depending on manufacturers, there can be extreme variance between the switching speed of converter, the power curve characteristics of the battery and the specific design of the battery management system (BMS). Any variation in these could produce very different load profiles when attached to a network and as such there is little insight currently into the effects of large scale EV adoption on low voltage networks.

If a single transformer has multiple EVs connected simultaneously, the total power may exceed the rated capacity of the transformer causing a voltage drop for all houses connected to that bus. If the EV's BMS is in constant power mode the reduced voltage will require an increase in current to meet the power demand. This increased current will further drop the voltage and the resulting end node voltage could fall below regulations. If the voltage drops out-with of the required limits there is a possibility of either under voltage protection being activated. If protection does not trip the line, there is a risk of equipment malfunction. Furthermore, prolonged under-voltage conditions in the grid would result in considerable fines for the system operators.

In addition to the larger currents drawn, EV chargers have an increased harmonic content that has been shown to cause excessive degradation in the local transformers reducing their lifespan [11]. In future, with smart metering, grid services may be designed to include voltage regulation and harmonic monitoring in low voltage networks. For the purpose of this research, it is assumed that all end nodes are appropriately loaded with voltage at charge points of 1.0 pu allowing a constant power draw from chargers at unity power factor.

2.1.2 Effects on Medium and High Voltage Network

The daily demand profile of the energy usage in a household as shown in the work of [23] shows a daily variation from peak to trough of 1.25kW to 0.25kW. With increased EV adoption and the predicted distribution of charging times as shown in the work of [9] it is likely to expect larger fluctuations in total demand as users arrive home around the 7:36PM mean time and add additional EV charging loads of 3-7kW to their household usage. With a larger fluctuation in the power demand it can be expected that the grid will require additional sources of fast switching generation and balancing mechanisms to sustain stable operation during the increased demand swings.

Due to the power electronic converters used to charge EV batteries their load is primarily a real power load with a power factor close to unity. The loads in reality are not purely real and contain a significant amount of harmonic distortion. These effects however do not cause any significant problems on the transmission network upstream of the transformer and so for the purposes of this research EVs are assumed to operate at constant real power with negligible harmonic distortion. The assumption of constant power is understandably not accurate with most BMSs providing different power responses to the battery state of charge. It has been assumed nonetheless in order to simplify simulations for a proof of concept and can be developed further in future work.

2.2 Grid Control Services

Most conventional power generation plants comprise of a spinning synchronous generator attached to a prime mover supplying mechanical input. The System Operators (SO) additionally has a supply of connected spinning reserves consisting of synchronous motors and connected mass (storage in rotational inertia). This allows the SO to store a large amount of energy in rotational energy ready to be converted into electrical power. The amount of energy stored is proportional to the square of the rotational speed of connected masses. This rotational speed is also proportional to the grid electrical frequency. As such the amount of excess energy in the grid stored in mechanical reserves is proportional to the square of the frequency. If the demand and supply of power into the grid are unbalanced, the total stored energy in the grid will reduce or increase causing the frequency to drop or rise and indicating a mismatch in generation to the system operators.

National Grid (SO) have a legal obligation to control system frequency at 50Hz plus or minus one percent[3]. To keep the frequency within these limits, national grid has multiple frequency response mechanisms that offer feedback to the frequency change by changing generation to match demand and recover the balance. The current markets available in the UK for grid balancing services are discussed further below with information supplied by National Grid and correct as of the 20th April 2018 [24] .

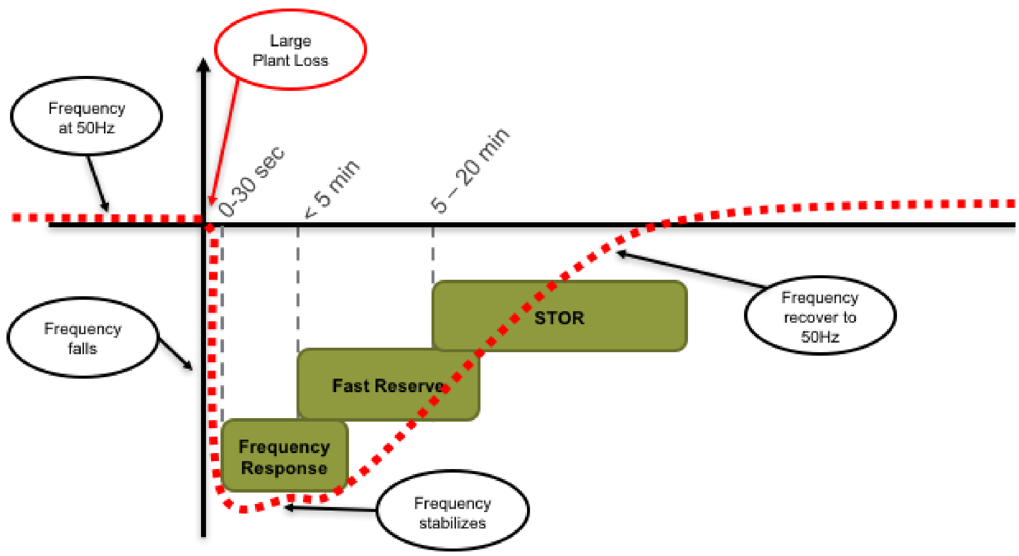


Figure 2.2: Demand Response to loss in generation.

In the event of a large scale loss in supply, the balancing services are triggered sequentially with the fastest and most expensive generation systems coming on-line first followed by cheaper alternatives as their response time allows. A block overview of the sequence of events following a loss in generation can be seen in Figure 2.2 where a significant source of generation is knocked out causing the drop in frequency that need be recovered using balancing service providers.

Table 2.2: Balancing Services Available to Demand Side Response (April 2018[24])

Service	Sub-service	Activation time	Duration	Min Power
Firm Frequency Response	Primary	10sec	20sec	1MW
	Secondary	30sec	30min	1MW
	High Frequency	10sec	indefinite	1MW
Reserve Services	Fast Reserve	2min	15min	50MW
	Short Term Operating Reserve	20min	2hr	3MW
	Demand Turn Up	custom	custom	1MW

2.2.1 Frequency Response

The grid frequency is directly affected by the amount of excess or deficiency in the supply of power to the grid. As such and because the frequency can be measured at any point on the grid, frequency is used as the primary measurement to ensure that there is sufficient generation in the network. Frequency response mechanisms detect when the frequency has exceeded a pre defined cut-off and then increase or decrease generation accordingly. The frequency is monitored in real time with two main categories of service offered in frequency response.

Mandatory Frequency Response

Mandatory Frequency Response (MFR) is the automatic change in active power to a change in frequency that is mandated on generation plants dependant on their size and location. MFR participants may still offer additional balancing services as long as these do not interfere with the plant's ability to supply MFR. The remuneration structure for MFR services consists of a holding payment (£/hr) for a unit's capability to provide the response and also a Response Energy Payment (£/MWh) for the energy used. Providers submit their own prices on a monthly basis and are selected accordingly due to demand required and the cost of supply. The size requirements for mandatory frequency response is dependant on location with national grid requiring greater than 100MW and Scottish Power only needing 30MW or larger.

Providers can offer one or any combination of the following response times

- **Primary Response**: Response provided within 10 seconds, sustainable for 20 seconds.
- **Secondary Response**: Response provided within 30 seconds, sustainable for 30 minutes.
- **High Frequency Response**: Response provided within 10 seconds, sustainable indefinitely.

Firm Frequency Response

Firm Frequency Response (FFR) is designed to counter the same incidents and changes in frequency as MFR but is openly available to any providers that can meet the service requirements. FFR can provide both dynamic (continuous second-by-second management of frequency) or static (discrete service trigger at defined frequency variation) responses with three response windows as with MFR. The minimum power supply required for FFR is 1MW with devices required to operate as either:

- **Dynamic Mode**: frequency sensitive.
- **Static Mode**: changing the output power via automatic relay .

The remuneration structure again has an availability fee (£/hr) and response energy fee (£/MWh). In addition also may contain a window initialisation fee(£/window) for each FFR nominated window and a nomination fee, a nomination fee (£/hr) that is a holding fee for each hour used inside FFR nominated windows. The same response times are expected as with MFR.

2.2.2 Reserve Services

Reserve services are used in addition to other balancing services to control the generation and consumption balance and the corresponding grid frequency. They are dispatched electronically and as such have a slower reaction time than frequency triggered response mechanisms. This however, enables reserve services to be triggered in the case that a change in demand or supply is expected but has not yet affected the frequency of the system. The response time of different reserve services varies extensively and so the different services are listed below in order of response time from fastest to slowest.

Fast Reserve

Fast Reserve is available to generation units connected to the transmission or distribution networks, storage providers and aggregated demand side response service providers. Fast reserve suppliers need to be available 24/7 with a greater likelihood of service between 06:00 and 23:00. The system conditions will dictate the frequency and length of dispatches that are on average of 5 minute duration and called upon 10 times per day. Providers are expected to deliver for up to 15 minutes, a minimum of 50MW at a delivery rate of 25MW/minute. The remuneration model uses a tendering process with fee structure consisting of an availability fee (£/hour), a nomination fee (£/hour used) and an energy fee (£/MWh).

Short Term Operating Reserve

Short Term Operating Reserve (STOR) services allow the connection of any technology capable of supplying 3MW of power to the transmission or distribution network by increasing generation or reducing consumption. Typically the service is used over two predefined availability windows ,morning window and evening peak window. If the service is required outside of these windows, providers can submit a bid for the usage that will be paid for utilisation but not availability. Within the availability window the payment would include an availability payment if used or not and a utilisation fee that covers energy expended. The maximum response time is 240 minutes, however due to the market, response times of less than 20 minutes are favourable as are locations surrounding high demand (south east England and Wales). The provider must be able to provide more than 3MW of demand turn down and sustain the response for a minimum of 2 hours to be eligible.

Demand Turn Up

The Demand Turn Up (DTU) service is open to users with an aggregated controllable load above 1MW that is used to balance out hours of low demand or high renewable generation. Providers are able to define the times and power rating available during specific hours or the "availability periods". The availability periods consist of the overnight window (23:30 – 08:30 for May, Sept, Oct and 23:30 – 09:00 Jun - Aug) and the weekend/bank holiday afternoon window (13:00 – 16:00 May-Oct). Outside of these windows providers are able to offer the service but will only be paid a utilisation fee and not an availability fee as would happen within the windows. In 2017 there was an average notice period of 6 hours 40 minutes with volume weighted average utilisation fee of £70/MWh [25]. Providers are not eligible to offer DTU at the same times as offering other balancing services and would be required to declare themselves as unavailable during the hours available for other services.

2.2.3 Demand Side Response

Demand Side Response (DSR) is the intelligent use of power by a business or household in order to offer relief to the grid on the response of a signal [24]. Most households and businesses are unable to meet the minimum power requirements of balancing services alone and the metering requirements pose a significant barrier to entry. With the Internet of Things able to control high power domestic appliances, it is now possible to aggregate a collection of households that when combined can satisfy minimum entry requirements. Through aggregation it is possible for the remuneration of a service to be split between the aggregator and device owners, in such a manner it is possible to build an economic model that is beneficial to all parties involved.

Provided there is adequate measurement systems and power supply, all the above mentioned services with the exclusion of mandatory frequency response are achievable using aggregated DSR but those with a durations longer than 1 hour are expected to cause additional inconveniences to EV users. These services will be the targeted during the design process of the scheduling algorithm due to their relevance.

2.2.4 Peak shaving

Peak shaving is not a balancing services as it is not contracted but rather encouraged through the use of time based consumption costs. By avoiding energy consumption during the times of peak system demand, users can reduce their energy bills and at the same time reduce requirements for the generation capacity of the grid. This is not a service offered by SOs or aggregators but rather, energy suppliers will typically offer "time-of-day" electricity tariffs to shift energy consumption from peak-demand with reduced costs of energy. This service allows users with time independent loads to schedule them at times of low demand and not only reduce ("shave off") peak demands, but also raise base loading. This reduction in the difference from peak to base load allows for more constant generation from conventional power stations that have slower reaction times and lower running costs.

This service is currently offered by various smart chargers and as a built-in service with newer EVs, where users can schedule in the cost of electricity and tariff times and the charging control will then decide when the cheapest time to charge is. In this report, it is assumed that the designed control for the provision of the grid-support services will be implemented on an EV that does not have peak avoidance services enabled.

2.2.5 Changes to Balancing Services

Throughout the research of this report the services offered by National Grid, in particular their technical requirements, were constantly changing to adjust to the developing markets. The services mentioned above are the fundamental services and although the details regarding technical requirements may change, they are correct as of the time of writing. These changes were initiated following an industry wide survey in October 2016 where: "*it was clear that change was needed – with the number of balancing service products and associated information provided .*" **Cathy McClay** Head of Commercial Electricity, National Grid[1].

The System Operator is looking now for the best ways to develop a more flexible electricity network that can make the most economic and efficient use of the resources available. Some of the highlights on the roadmap [3]are:

- standardising existing products (FFR, STOR, FR)
- introduction of faster-acting response products to meet the SO's needs
- a trial of closer to real-time procurement system
- review of contracts and standards to lower entry barriers

With the expected changes to the structure of services the system, a design for a specific service may not be effective for long and so the algorithm was designed to provide a generic power shift that can be applied to a range of the key services. The targeted service provided by a fleet of aggregated electric vehicles is therefore, **a bidirectional demand change of minimum 1MW that can be sustained for up to one hour and has a response time of less than 10 seconds.** As such the desired service provided shall be classes as:

- **Demand Turn Down -** Real power flow from grid to vehicle is reduced

- **Demand Turn Up -** Real power flow from grid to vehicle is increased

[3]A full overview of the current services and roadmap can be found in appendix

2.3 Grid Balancing capable technologies

There are currently various technologies capable of providing balancing services. Some are designed primarily for this purpose, others to offer balancing as a secondary service to provide an alternative revenue stream for owners and balancing capacity to system operators. The use of an aggregated EV fleet to provide grid services could allow automotive OEMs to monetise already sold assets and concurrently provide a payback to owners for the use of the service. This additional revenue stream would help to solidify the business models of manufacturers moving into the electrified automotive sector and at the same time provide remuneration based incentives to the owners all through offering a stabilising mechanism to grid system operators. The range of technologies currently used was explored with particular focus on response times and durations of service.

2.3.1 Synchronous Generators

Power plants with synchronous generators consist of a prime mover (mechanical power source) with variable control and the synchronous generator that with additional controls can adjust the power factor and output voltage of the system. Depending on the size and location of a power plant it may be required to provide mandatory frequency response (MFR). This is an automatic response of the output active power to a change in grid frequency. The characteristics of this mandatory response to a disturbance is vastly different for different prime movers dependant on their ability to vary mechanical power output. The range of responses to a demand disturbance of 5% is at fastest, a response time of 5 seconds and settling time of 20 seconds with hydro-power, and slowest a response time is 25 seconds and settling time 68 seconds in thermal plants. The use of such systems for generation above ideal capacity comes at the cost of lowered fuel efficiencies. This increased cost dictates that bids be above a threshold to prevent mandatory frequency responses running at a loss during the service offering.

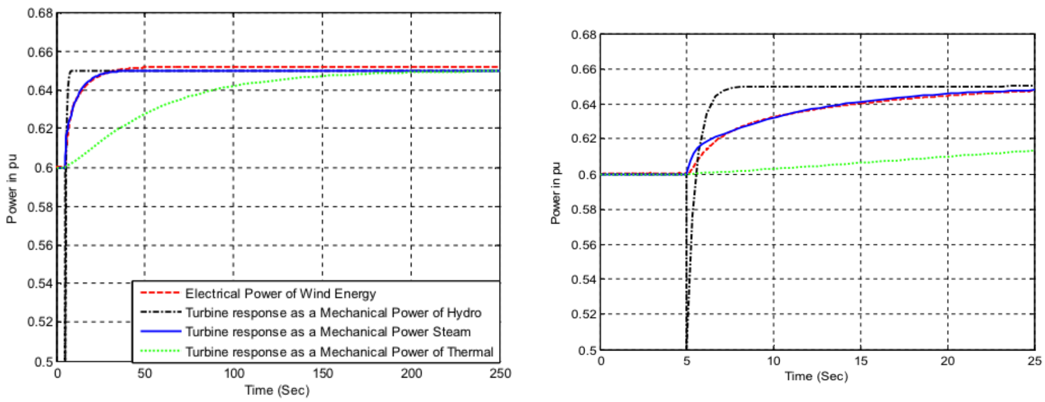


Figure 2.3: Power response of turbine based synchronous generators to a 5% load disturbance [5].

2.3.2 Large scale battery storage

With the price of lithium-ion batteries dropping 73% between 2010 and 2016, the cost of industrial scale battery storage services has reduced significantly [26]. This has meant that energy storage through batteries has become economically viable with approximately 25% of the 100MW installed capacity coming online in 2017 [27]. These storage systems offer response times of both demand turn up and demand turn down faster than any conventional power source with a record response time of 0.14 seconds by the 129MWh Tesla battery in South Australia in 2017 [28]. The round trip efficiency of lithium storage systems is below 85% [20] and as such despite lower running costs and no fuel requirement these systems run the risk of operating at a loss if bid margins are too low.

2.3.3 V2G and smart chargers

High end electric vehicles have battery capacities up to 100kWh [29] with new charging facilities being exploited for demand response using aggregated bidirectional chargers. By aggregating a fleet of vehicles equipped with V2G chargers, a virtual power plant the size of the sum of its parts is able to be contracted to the system operators with the remuneration fed back to vehicle owners and aggregators.

These chargers can switch between supplying the grid with reinforcement, when required, and charging the vehicle battery ready to be driven. If installed in a private residence these systems usually have a maximum power flow of 7kW and need to be aggregated to meet minimum power requirements. Most new EVs are connected through 3G or LTE as a minimum [30] and so are able to react to signals in the same time as large scale battery storage systems with the addition of the connectivity latency of between 98ms and 212ms [31]. This response time of less than one second allows V2G fleets to be used in any of the DSR services mentioned in table 2.2 provided the fleet can supply the minimum power requirements.

The first publicly available V2G chargers are to be released in Q2 or Q3 of 2018 in a joint venture between Ovo Energy suppliers and Innovate UK. These chargers are only available to Nissan Leaf drivers with results expected by the end of 2018[13]. One significant hesitation from owners is that of battery degradation due to the finite number of cycles of a battery before the range is significantly affected. Additionally with a round trip efficiency of less than 90% and the possibility of the service being called during peak tariff hours it is possible for the grid services to increase the running cost by more than the remuneration passed on by the aggregators.

2.3.4 Internet of Things aggregation platforms

There are many other mechanisms of demand response that utilize an Internet of Things to control and aggregate domestic appliances for grid services. These platforms utilize the smart connectivity of household items such as water heaters and washing machines that when multiplied by thousands of users allow the service provider to compete in a demand response market.

One noteworthy such system is the Alphabet's Nest®smart thermostats. The owners of Nest products have the option of opting into a "Rush Hour" scheme where by shifting their times of energy usage customers receive income from their energy providers [32]. The energy providers can halt the climate conditioning in thousands of houses and as such receive the income associated with the services they are offering to the grid. A portion of this income is then passed onto the end customer and provides a much cheaper method of demand response than running a fuel consuming power station.

One case where this system was extremely useful was on 21 August 2017 in the United States where a large portion of the country saw a total eclipse of the Sun. This predictable event was estimated to knock out 9GW of solar power generation in a period of minutes. For California 40% of demand is frequently met by solar generation and so this posed a major threat to the grid during the event [32]. Nest thermostats were able to, on the day of the eclipse, pre-condition over 750 000 houses allowing Nest as an aggregator to reduce energy demand by 700 MW. This mechanism of delayed load has the potential to be extremely profitable to users, if the time of day that the load is moved to does not increase the electricity tariff, there is no running cost or additional maintenance required by home users and any income generated is a by-product of a load that would always have been used.

2.4 Summary of Demand Response and EVs

Having reviewed the more common grid service providing technologies, it is apparent that the more conventional the technology the higher the running costs and necessary bid to be economically feasible. The synchronous generation devices have the added advantage of a tried and tested system with certified measurement protocols and the ability to additionally provide reactive power that power electronic devices will struggle to do. The downsides to these larger generators and battery storage systems is that they are dedicated to this service and are required to be significantly profitable through higher bids. Utilising fleets of EVs or household appliances and demand shifting on the other hand only requires income to equal the cost of running the aggregation system and so in theory will allow for much lower bids and a more competitive marketplace.

By utilising unidirectional and not V2G fleets of vehicles it could be possible to reduce total energy consumption by removing round trip losses and battery degradation through less cycles. The unidirectional fleets are able to be controlled by an entirely cloud based system, while plugged into any charge point vehicles can still provide the same functionality and do not require dedicated bidirectional power electronics.

3 Behavioural Profiling

In order to calculate the number of vehicles that are at home and their relevant state of charge, it is necessary to attempt to predict the profiles and driving styles of EV users. This classification and grouping would allow broad matching to demographic profiles to behavioural traits, when combined with the portions of the driving fleet they occupy this would allow a more accurate model of the availability of the fleet and corresponding demand response service capabilities.

3.1 Driver Profiling

To create the fewest groups and at the same time cover the largest variation in driver behaviours, the drivers have been classified depending on the function for which they use the vehicle, their age, gender and whether or not they own the vehicles. The categories were seen to be the most significant from analysis on the UK population [6].

3.1.1 Profiling with respect to function

To predict the travel patterns, it is necessary to analyse what are the reasons for driving. From the reasoning it is possible to predict the tasks that will make up the base load of daily driving and those which will be sporadic. Using the results from the 2016 National Travel survey for England in 2016, it is possible to see that 35% of the distances travelled in a year are due to trips for commuting, business and education (incl. escorting), Figure 3.1. These activities are a necessity for most households to complete on a week-daily basis and can therefore be used to predict the base vehicle usage during weekdays. Weekend predictions are far more complex with users having less repetition in their schedules and so it is predicted that for a real life application calendar analytics and machine learning will be used to predict these behaviours. For the purposes of this research only the base driving load for standard weekdays will be analysed due to insufficient data that would allow accurate weekend predictions.

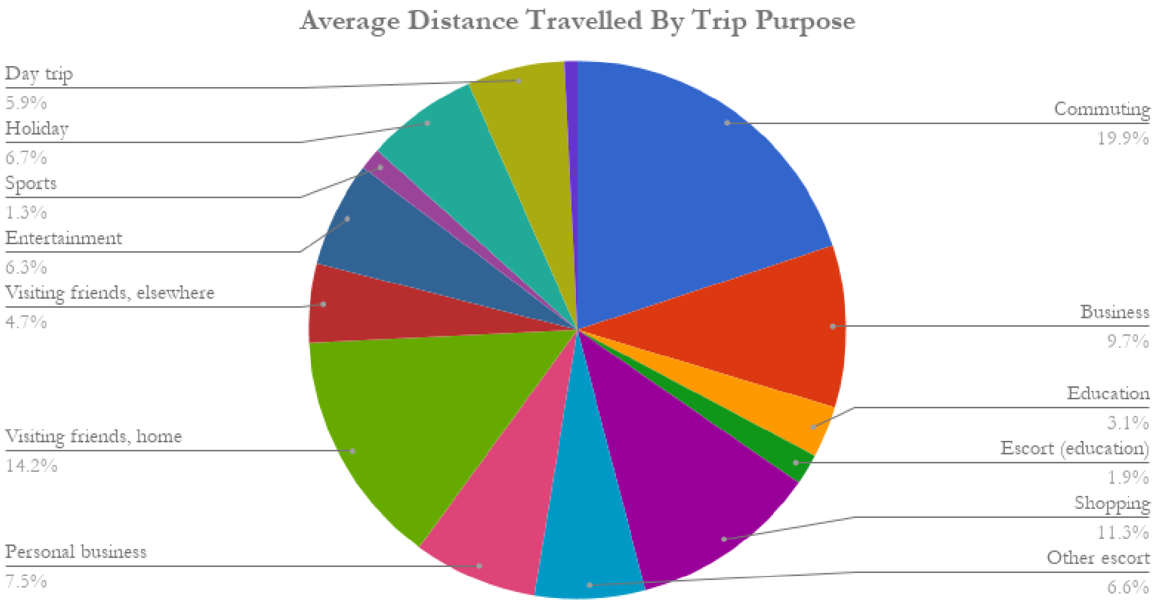


Figure 3.1: Average distance by trip purpose [6].

Through the correlation between traffic volume and road congestion it was possible to determine a basic relationship between the average distance travelled during weekdays and on weekends. This relationship is not expected to be entirely accurate but simply aid towards providing initial conditions for later simulations where sensitivity analyses will be conducted. By taking the integral of all traffic throughout the week and comparing the total distances driven on weekdays to weekends it is possible to find a correctional ratio comparing weekday and weekend average travel to the daily average throughout the year, Table 3.1.

Table 3.1: Comparison of weekday and weekend traffic levels in Edinburgh.

	Average Traffic Level	**Percentage of Total Traffic**	**Ratio to Daily Average**
Weekend	13%	18%	64%
Week Day	23%	82%	115%

With the four base purposes identified to account for 35% of the annual travel and weekday travel accounting for 116% of the daily average it was calculated that the average weekday base load can be found to be 40.6% of the daily average distance, Equation 3.1.

$$X_{Base} = 35\% * 116\% * X_{average} = 40.6\% X_{average} \quad (3.1)$$

3.1.2 Profiling with respect to Age and Gender

There is a significant differences in travel behaviours based on the age and gender of drivers with driving distance peaking in the 50-59 age group and higher for men than women in every age group other than 17-20 [6]. Accordingly, to specify the user profiles as accurately as possible, their age group and gender have been selected as significant distinguishable characteristics of EV drivers.

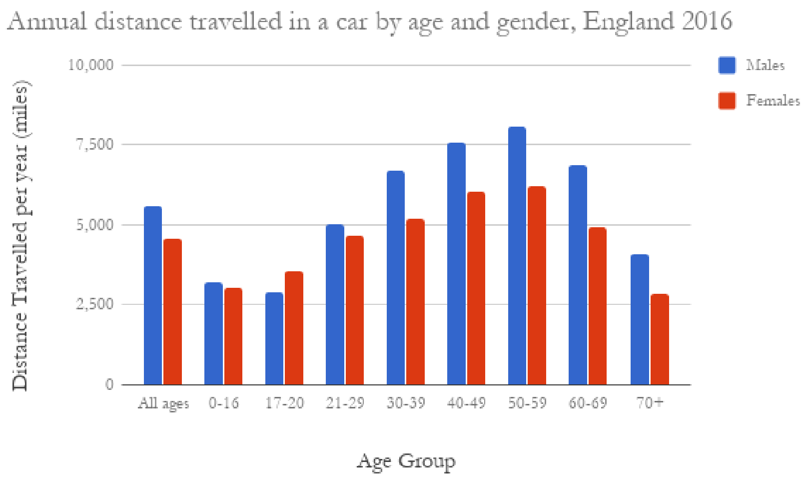


Figure 3.2: Average annual distance travelled by age group [6].

The expected target market user, based on the sale statistics of the Jaguar I-Pace[4], are males from the ages of 30 - 59 [29]. Using this data on the age ranges, the corresponding driver use cases are selected to be between 21-39 and 40-59. By weighting the sub groups used for the survey [6] according to the sample size for each sub-group, the average annual distance travelled by age and gender was found, Figure 3.2.

Table 3.2: Average annual distance travelled by car respect to age and gender.

Age Group	Gender	Average Distance (miles pa)
21-39	Male	4927
21-39	Female	3146
40-59	Male	7126
40-59	Female	4183

[4]This stage of research was conducted under the assumption of support from JLR throughout the project and thus designs were initially tailored to work with a fleet of their vehicles

3.1.3 Profiling with respect to vehicle ownership

Despite composing of only 3% of the sample, the annual mileage of company cars was 250% over that of privately owned cars 3.3. Together with the larger proportion uptake of electric vehicles by companies, through tax incentives and other government relief subsidies, indicates that companies with EV fleets are a key sector and that EV ownership should be considered in distinguishing EV user profiles. Additionally, 35% of the mileage of company cars are attributed to commuting, an activity that is a predictable portion of the weekday base load.

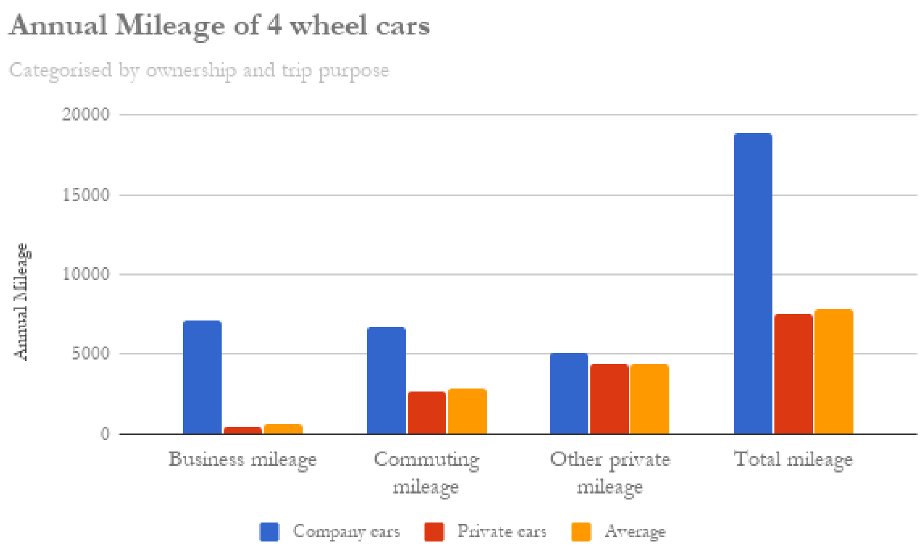


Figure 3.3: Annual mileage of 4-wheeled cars by ownership and trip purpose [6].

To fit the user profiles, the average distance travelled by private vehicles relative to company owned vehicles was extrapolated to fit the distance travelled by age and gender. This ratio then allowed the annual distances for company owned vehicles to be calculated by assuming all grouping by age and gender maintain the same ratio to ownership average, Table 3.3.

Table 3.3: Annual driving distances by car as driver by age, gender and vehicle ownership.

Ownership	Age Group	Gender	Annual Distance(miles)
Private	20-39	Male	4927
		Female	3146
	40-59	Male	7126
		Female	4183
	Average	**N/A**	**7500**
Company	20-39	Male	12416
		Female	7927
	40-59	Male	17957
		Female	10541
	Average	**N/A**	**18900**

3.2 Conclusions on Driver Profiles

The above analysis shows that there are significant differences between the user groups defined through age, gender and vehicle ownership. This would have allowed sample data provided to be categorised and is expected to have returned results showing the driving behaviours and usage patterns of EV users that could then be fed into the simulations. This was not possible due to a lack of reliable input data spread across the range of user groups. To still be able to analyse the potential for using EVs with unidirectional chargers to provide the same grid services as V2G connected systems the assumptions will be based on fleet-wide data from public sources in order to form a starting point for fleet synthesizing assumptions.

4 Data Analysis

This research was initially begun under the impression of being able to receive real travel data from ICE users collected through phone application and converted to simulate an EV. Due to legal implications and IP protection the original source was unable to supply the required data. This prevented a the ability to test the algorithm on a real life fleet, instead a collection of open source and public data was collected to try and simulate a fleet as accurately as possible. The data sources contained a large range with certain sources allowing for higher accuracy predictions and models for specific EV traits, others a broader range of travel behaviours more applicable to ICE vehicles than EVs.

4.1 Data Sources

The primary focus of the data search was to build assumptions for the basic requirements of the simulation algorithm fleet. The required specifications were:

- Battery Size
- Charge Rate
- Daily Usage
- Arrival Time
- Departure Time
- Typical Arrival SoC
- Typical Required SoC for Departure

The main sources analysed are discussed below with justifications as to the assumptions of the EV fleet. The primary assumption was to design the EV fleet specifications around the most commonly sold BEV in the UK, Nissan Leaf [33]. The vehicle would charge at home using a single phase 13A outlet.

4.1.1 National Travel Survey

The National Travel Survey is a household survey of conducted by the **Department for Transport** annually since 1988. The survey targets residents of England that travel within the UK and is collected from interviews and a one week diary in some cases. The data was used to form the basis of the definition of user groups as primary research and preparation with the expectation of receiving real life data and as such did not form a major part of the assumptions for the simulated fleet. The data is comprehensive and well documented but does not distinguish between EVs and ICE vehicles meaning that it wasn't the best suited collection to use when defining the simulation fleet.

4.1.2 Google Maps

Google Maps®is an application centric company underneath the Alphabet®umbrella that allows users to lookup a large range of locations and receive directions to that location from their current position. With over 2 Billion active monthly users [34] and the ability to download all historic data in a readable format this is a worthy source of location data. The data is not publicly available but was collected from three sample users and analysed to see if it would be worthwhile collecting a larger number of samples. The data points were found to include time-stamps, latitude, longitude, heading and activity but were not continuous with regards to the time line. This produced erroneous results after processing with the location of a user not recorded if they were not using the application. As such a large majority of daily commutes, where directions were not needed, did not get recorded and the so it was decided to use a proven distribution for arrival and departure times [9].

4.1.3 My Electric Avenue

One of the uses of the £30 Million invested by the UK government into the Innovate UK research into V2G applications was a project carrying out trials to discover the impact that charging clusters might have on local (Low Voltage) electricity networks during peak hours [7]. The project analysed a fleet of 200 Nissan leaf's and their affect on local substations for 2 years recording all trips and charging times. The primary takings from this dataset were those pertaining to the SOC when vehicles arrived and departed, Figure 4.1.

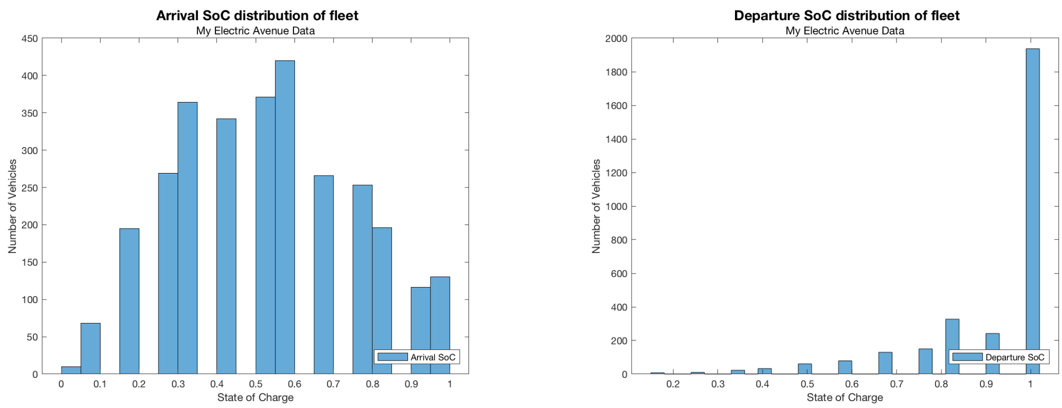


Figure 4.1: Distribution of Fleet State of Charge [7].

The concluding result used in the simulation assumptions from this dataset was that of the vehicle arrival and departure State of charge that were assumed to be 50% and 90% respectively. The standard deviation of the dataset was considerable large compared to the mean values, Table 4.1. To compensate for this sizeable error margin the assumptions were tested with sensitivity analyses that varied the arrival SoC from 15% to 87.5%.

Table 4.1: Arrival and Departure State of Charge From Sample Fleet [7].

	Mean	**Standard Deviation**
Arrival SoC	51.79%	25.10%
Departure SoC	90.08%	17.77%

4.1.4 TomTom - Edinburgh Traffic Levels

TomTom®began as a consumer electronics company that strived to "*created the easy-to-use navigation device*" [8]. Since then, they have spread out into a larger range of consumer electronic devices and services all centered around connectivity and global positioning systems. Through the anonymous data collected on these devices TomTom is able to measure traffic flows and speeds throughout the UK. This data is displayed on their connected devices to inform users and can also be viewed on their website displaying the previous 48 hours in a city of choice. The traffic levels for Edinburgh were collected over a period of weeks and allowed average traffic patterns to be detected for weekends and weekdays, Figure 4.2.

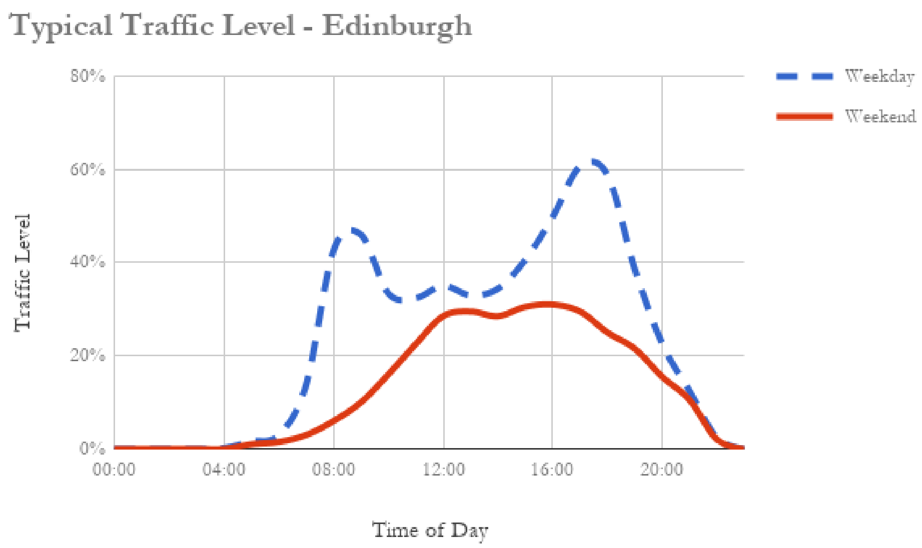


Figure 4.2: Typical Traffic Levels in Edinburgh 2018 [8].

This data was used in the user profiling to compare weekday travel and weekend travel in an effort to evaluate whether the collections should be distinguished or averaged. The results varied significantly between weekends and weekdays with Friday afternoons being marginally out from the other weekdays. The traffic flows is expected to have a correlation to the presence of vehicles at home or arrival and departure times but this was not considered to be the most acute method of calculating arrival times. This data provided insight into the profiling of potential drivers but was not used in the simulations.

4.1.5 Tesla Motors Club

Tesla Motors Club LLC [35] is an independent enthusiast organization and is not affiliated with Tesla Motors, Inc. or its subsidiaries. The primary use of the forum is to share information amongst EV users and in particular Tesla vehicle owners. One significant discussion is that regarding battery degradation and the causes. For this there is a crowd sourced database that users record their vehicle type, purchase date, mileage and specifics regarding the range of the vehicle following a charge. The results of this show that EV users in the UK drive on average 65 miles per day, Table 4.2, compared to the national travel survey average daily distance of 13.9 miles [6]. This variance is significantly large to cause concern regarding the validity of one or both the sources. When compared to the dataset of [7], the Tesla Motors Club data was of a much smaller UK sample and not the target vehicle, as such, it was disregarded with respect to the basis of assumptions.

Table 4.2: Crowd Sourced Average EV Daily Driving Distance.

	Users in Sample	**Average Daily Usage (miles)**
Asia, Pacific & Europe (excl UK)	277	97.3
Canada	19	73.4
USA	107	53.2
UK	11	65.2

4.2 Fleet location Assumptions

All scheduling models require a prediction or recording of vehicle locations defined in simplest form under boolean logic: at home or not at home. The user profiling thus far predicts only the daily driving distance, with no data sources that distinguished the different profiles with respect to their daily arrival and departure times.

The collected Google Maps data set was too small and did not represent the range of the user profile demographics making it difficult and inaccurate to use for the basis of the simulation arrival and departure times. It was decided to rather use previous literature defining the distribution of these times and vehicle locations. The predominantly cited work, in the research found, used a distribution profiling with the data collected by [36] and model developed by [9]. This distribution models the arrival and departure of vehicles with a normal distribution assuming a single trip per day. The arrivals are centred around a mean of 19.62 and standard deviation of 3.62. The departure times have a mean of 10.53 and 3.26 standard deviation, Figure 4.3.

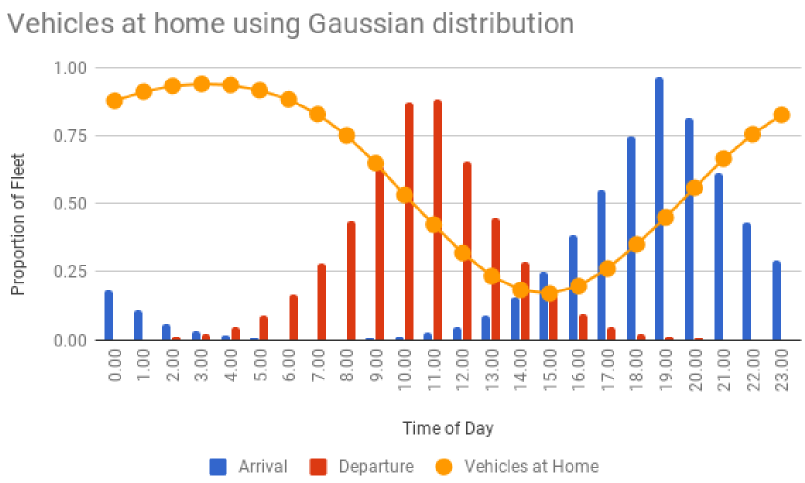


Figure 4.3: Proportion of Vehicles at home - Theoretical Results [9].

The collected location data results were compared to the theoretical distribution despite being of insufficient credibility, Figure 4.4. There was additionally no method found in previous work that accurately converted location proportions to arrival and departure times without the continuous time steps in the sample data. As such so for initial simulations the arrival and departure distribution used was that of [9].

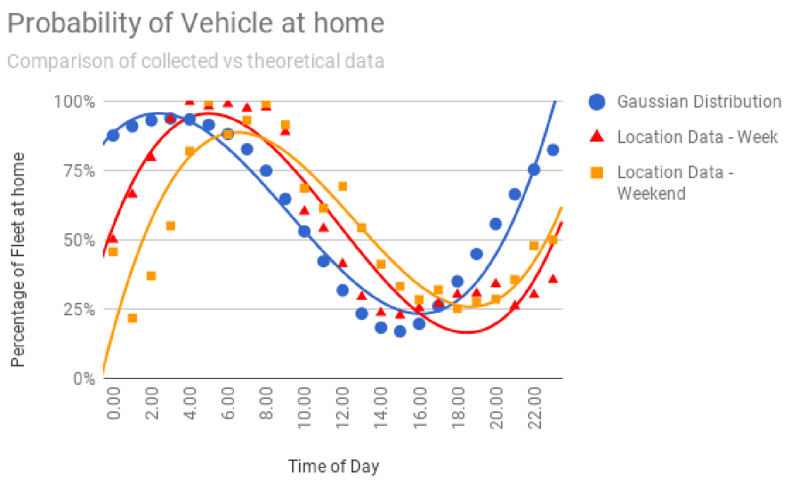


Figure 4.4: Proportion of Vehicles at home - Theoretical vs Collected Results.

5 Fleet Simulations

To control the the vehicle state first requires the analysis of the vehicle locations and state of charge. The following structure was utilised for all scheduling algorithms with the priority function adjusted to accommodate the different models. The SoC of vehicles and availability vary throughout the day, yet a demand response contract requires a constantly available source of power to be called upon at any time of day. For this reason, the target result is defined as a scheduling algorithm that provides the highest availability of both demand turn up and demand turn down services at the hour of lowest availability.

5.1 Fleet Composition

The EV fleet was synthesised based on the analysis of various data sources aggregated to provide the most accurate predictions around specific traits. The final assumptions used for the simulations were designed around the specifications of a Nissan Leaf as follows:

- Battery Size: 40kWh
- Charge Rate: 3kW
- Arrival SoC: 50%
- Required SoC for Departure: 90%
- Arrival times: normally distributed(mean 19.62; standard deviation 3.62)
- Departure times: normally distributed(mean 10.53; standard deviation 3.26)

5.2 Simulation structure

The structure of the simulation ran the same dataset through a range of different priority based scheduling functions. To make the code as modular as possible, the structure utilised blocked functions where the simulation looped through each vehicle independently. Within the loop for each vehicle it ran through a 24 hour cycle beginning in the hour of arrival. During each hour the vehicle was checked for location, then charge priority was calculated after which the vehicle charging state determined, Figure 5.1. The only change required between simulations was the priority function and fleet composition allowing different scheduling methods to be tried against different fleets. This approach was chosen in order to achieve more consistent results through the minimisation of human errors in changing between scheduling methods and simulation parameters.

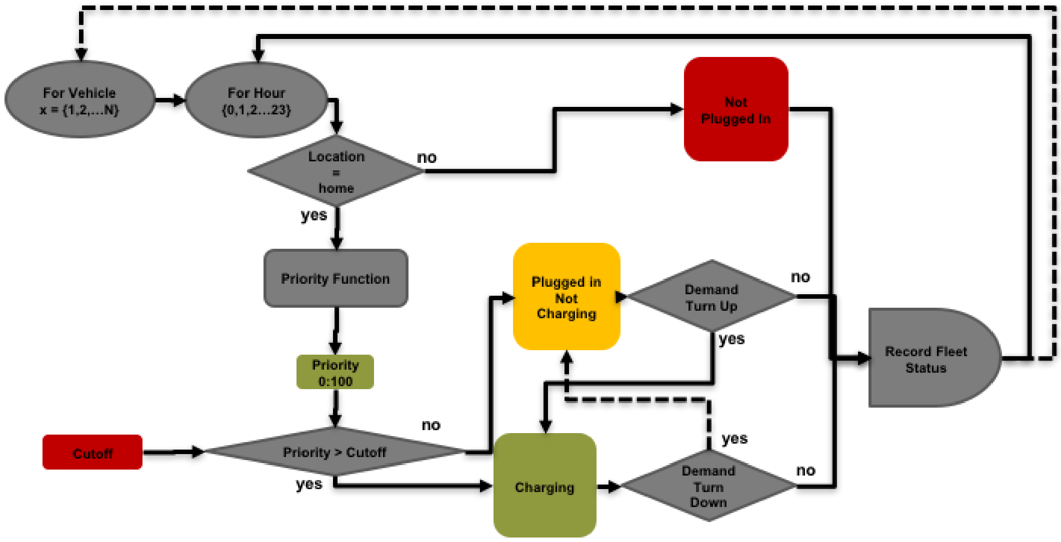


Figure 5.1: Algorithm Structure Block Overview.

5.3 Vehicle location Function

To calculate the location of the vehicle, the function first checked if arrival and departure occurred on the same day by checking if the arrival time was greater than departure time. If arrival and departure occurred on the same day then the vehicle was at home if the current hour was between that window. Else if the vehicle arrival time was larger than departure time it mean the vehicle arrived the following day and then then vehicle was deemed to be at home if the current hour was either smaller than the departure time or greater than the arrival time.

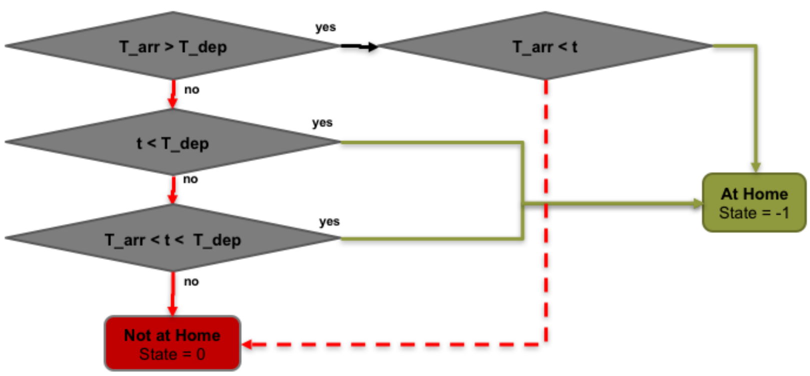


Figure 5.2: Vehicle Location Function.

It was assumed that the vehicle was plugged in upon arrival and remained plugged in for the duration of the time at home. If at home the vehicle was given a state of -1 indicating that it requires prioritising, else the vehicle received the charging 0 deeming it unable to participate.

5.4 Priority Function

The priority algorithms select which vehicles charge or do not charge and thus are available for demand turn up or demand turn down at specific times of the day. The functions determine the priority of a specific vehicle to charge out of 100 whereby the charge function will determine the charging state of the vehicle. The different scheduling functions were customised to meet alternative criteria and allow for different numbers of EVs to be charging or not charging and plugged in respective to the time of day. All priority algorithms were checked post-simulation to ensure that the total energy required for charging was still met to within 5% and that no simulation could charge more vehicles at any one time than were present at home.

5.4.1 Ideal – Best Theoretical model

The best theoretical power output through scheduling is one that has the largest minimum value throughout the day while still achieving a correct energy balance for the number of vehicles and their relative state of charge on arrival and departure.

$$P(t) = P_{threshold} \lim_{\to\infty} \tag{5.1}$$

$$\int_{0}^{24} P(t)dt = \sum_{i=1}^{N} Batt_{size} * (SoC_{dep} - SoC_{arr}) \tag{5.2}$$

By solving simultaneously for equations 5.1 and 5.2 the resulting answer produced a power function respective to time that is constantly equal to the threshold power. This result, is not physically possible due to the limitations in fleet availability.

$$P(t) = \frac{P_{max}(t)}{2} \tag{5.3}$$

To not exceed the fleet availability, an additional constraint of only using half the available fleet is required to allow equal demand turn up and demand turn down power at any time. With the addition of equation

5.3 the ideal power profile is established to maximise demand response capabilities equally up and down as shown in the Ideal function, Figure 5.3.

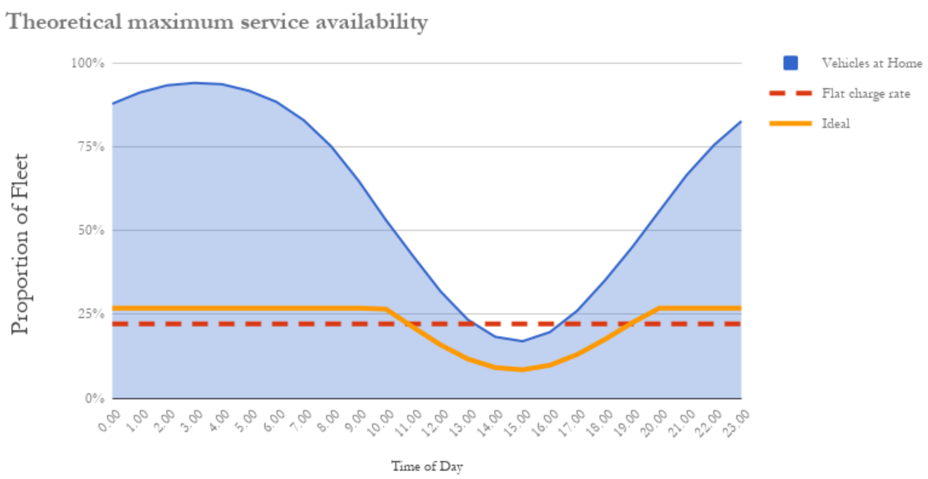


Figure 5.3: Maximum Theoretical Fleet Availability for Demand Turn Down.

5.4.2 Charge as soon as possible (ASAP)

This scheduling function assumes that vehicles begin to charge as soon as possible once they arrive at home. In doing so the vehicles are ready the fastest and the final SoC is least likely to be below 90% because of any demand response.

- Vehicles charge to 90% SoC and are available for Demand Turn Down until this point.
- After 90% SoC, vehicles remain plugged in until departure and are available for Demand Turn Up for 1.3 hours (4kWh at 3kW).

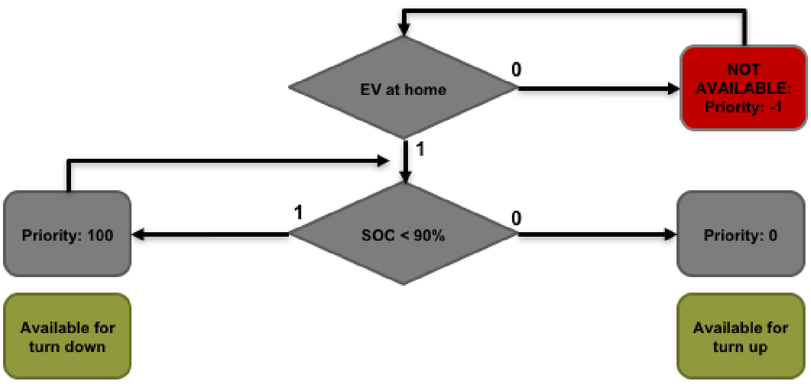


Figure 5.4: Charge ASAP Function Overview.

5.4.3 Charge as late as possible (ALAP)

This scheduling function assumes that vehicles begin to charge as late as possible, but are still charged to the required 90% SoC charge on departure provided they are not disrupted during charging. This service offers the lowest guarantee on required charging being completed but offers the largest chance of demand turn up being used in the time before the vehicle was scheduled to charge.

- The vehicle's latency was calculated by the difference in the time remaining before departure and the required time to charge the vehicle. If the latency was below 1 hour, the vehicle would be charged.
- Vehicles wait to charge and are available for Demand Turn Up until they begin to charge and as such are unavailable for Demand Turn Down
- Once charging begins, the vehicle will charge to 90% and then depart. While charging vehicles are available for Demand Turn Down.

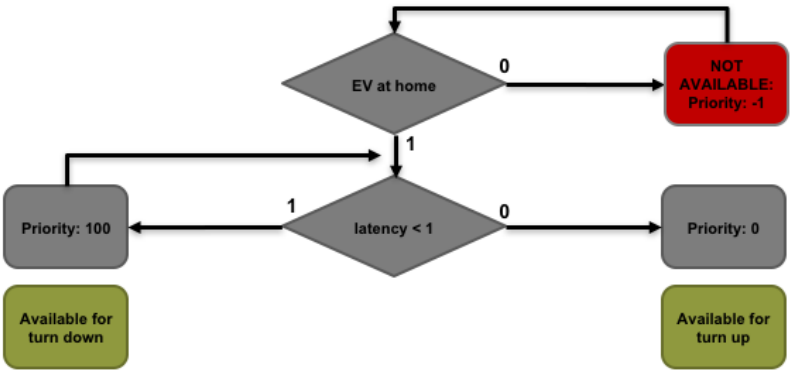


Figure 5.5: Charge ALAP Function Overview.

5.4.4 Midpoint scheduling (MidP)

This algorithm splits the fleet into two equal parts and treats one half with the charge as soon as possible (ASAP) model and the other half with the charge as late as possible (ALAP) model. In doing so it is predicted that the overlapping times of least availability for one method and most availability for another will enable a balanced fleet availability throughout the day. The algorithmic design utilises the functions for ALAP and ASAP and simply halves the fleet size to each and prioritises vehicles accordingly. If used to control a fleet, the vehicles would alternate between ASAP and ALAP on consecutive days to ensure equality amongst drivers and minimise disruption to users.

5.5 Charging Function

The charging function was designed in order to be able to prioritise the vehicles with more incremental steps determined by the SoC, latency and time plugged in. Due to the results achieved using the MidP scheduling it has been unnecessary to develop the adaptive priority cut-off that would have allowed only the top portion of a fleet to charge and so instead the function was run in the simplest manner with a fixed priority. With a fixed priority the charging function simply tests if the priority of a vehicle is above a cut-off priority and then sets the vehicle state accordingly. It was deemed unnecessary and overly complication to use states 4 and 5 as the functionality between these states does not differ with unidirectional chargers; as such the output state for no service was used in these cases.

Table 5.1: Charging State Table.

Input State	**Priority**	**SoC**	**Output State**		
			No Service	**Demand Turn Down**	**Demand Turn UP**
0	*	*	0	0	0
-1	below cutoff	<95	1	1	**<u>6</u>**
		>95	1	1	1
	above cutoff	*	2	**<u>3</u>**	2

5.6 Results from initial simulations

The simulation was run with 5,000 EVs and results normalised to a proportion of the fleet available for demand turn up and demand turn down services, Figure 5.6 and 5.7. Having established the power achieved with a fleet of 5000 vehicles, the proposed fleet size required per MW of response contracted was extracted, Table 5.2.

Table 5.2: Fleet Size Requirement for 1MW Aggregated DSR.

	ASAP	**ALAP**	**MidP**	**Ideal**
Demand Turn Up	13,387	15,152	4,040	3,917
Demand Turn Down	54,645	111,111	3,801	3,917

5.6.1 Demand Turn-Down

The results show that, as expected, the ASAP algorithm leaves a large time period between 06:00 and 12:00 where there is only 0.6% of the fleet available for demand turn down at the lowest point in time. This is comparable also to the ALAP algorithm that had 0.3% availability for demand turn down between 18:00 and 23:00.

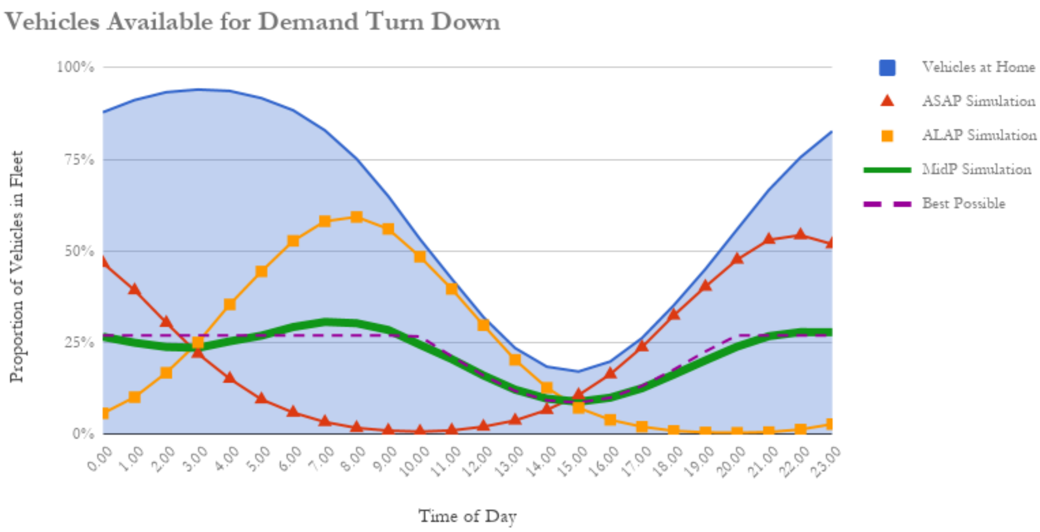


Figure 5.6: Vehicles Available for Demand Turn Down.

The midpoint scheduling algorithm achieved largely better results with the minimum availability in line with the time of minimum vehicles at home. The algorithm provided a minimum service availability of 8.8% compared to the theoretical best of 8.5%.

Table 5.3: Minimum Fleet Availability for Demand Turn Down.

	ASAP	**ALAP**	**MidP**	**Ideal**
Minimum availability	0.6%	0.3%	8.8%	8.51%

5.6.2 Demand Turn-Up

The results for the turn up services show again the ASAP priority algorithm with an extremely low minimum availability of 2.5% at 18:00 and the ALAP lowest point being 2.2% at 12:00. These values are higher than those for the demand turn down service but still significantly lower than the ideal value of 8.5%.

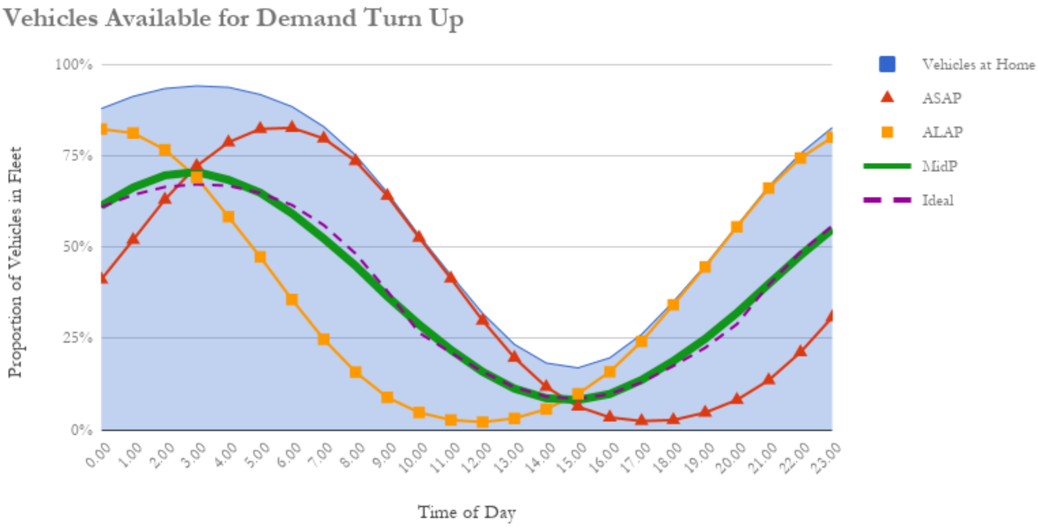


Figure 5.7: Vehicles Available for Demand Turn Up.

The midpoint priority algorithm proved more successful with a minimum availability of 8.3% and an RMS error compared to the ideal of 1.46%. The largest deviation was 3.7% at 07:00, however, this is of no significance as more than 50% of the fleet was available for demand turn up during this hour.

Table 5.4: Minimum fleet availability for Demand Turn Up.

	ASAP	ALAP	MidP	Ideal
Minimum vehicles available	2.5%	2.2%	8.3%	8.51%

5.7 Sensitivity Analysis 1

To determine the effects that an error in the assumptions would have on the result, a sensitivity analysis was conducted to vary input criteria and observe resulting changes in output. All simulations used 5,000 vehicles in a fleet with the same arrival and departure times as original simulations. The fleet characteristics that were altered were the Battery Size, Charge Rate, Arrival and Departure SoC. 20 simulations were run and the input criteria can be seen in Table 5.5.

Table 5.5: Sensitivity Analysis Simulation Details.

<table>
<tr><th>Simulation</th><th>Arrival SoC</th><th>Departure SoC</th><th>Battery size (kWh)</th><th>Charge Rate</th></tr>
<tr><td>1</td><td>50%</td><td>90%</td><td rowspan="5">40</td><td rowspan="10">3 (kW)</td></tr>
<tr><td>2</td><td>40%</td><td>90%</td></tr>
<tr><td>3</td><td>40%</td><td>80%</td></tr>
<tr><td>4</td><td>30%</td><td>80%</td></tr>
<tr><td>5</td><td>30%</td><td>70%</td></tr>
<tr><td>6</td><td>50%</td><td>90%</td><td rowspan="5">20</td></tr>
<tr><td>7</td><td>40%</td><td>90%</td></tr>
<tr><td>8</td><td>40%</td><td>80%</td></tr>
<tr><td>9</td><td>30%</td><td>80%</td></tr>
<tr><td>10</td><td>30%</td><td>70%</td></tr>
<tr><td>11</td><td>50%</td><td>90%</td><td rowspan="5">40</td><td rowspan="10">7 (kW)</td></tr>
<tr><td>12</td><td>40%</td><td>90%</td></tr>
<tr><td>13</td><td>40%</td><td>80%</td></tr>
<tr><td>14</td><td>30%</td><td>80%</td></tr>
<tr><td>15</td><td>30%</td><td>70%</td></tr>
<tr><td>16</td><td>50%</td><td>90%</td><td rowspan="5">80</td></tr>
<tr><td>17</td><td>40%</td><td>90%</td></tr>
<tr><td>18</td><td>40%</td><td>80%</td></tr>
<tr><td>19</td><td>30%</td><td>80%</td></tr>
<tr><td>20</td><td>30%</td><td>70%</td></tr>
</table>

From this sensitivity analysis and results in it was found that across the range the MidP algorithm was closer to the ideal than either the ASAP or ALAP. When using EVs that had daily charging times below four hours, the minimum demand turn down availability was significantly reduced, Figure 5.8. To further explore this relationship an additional sensitivity analysis was conducted.

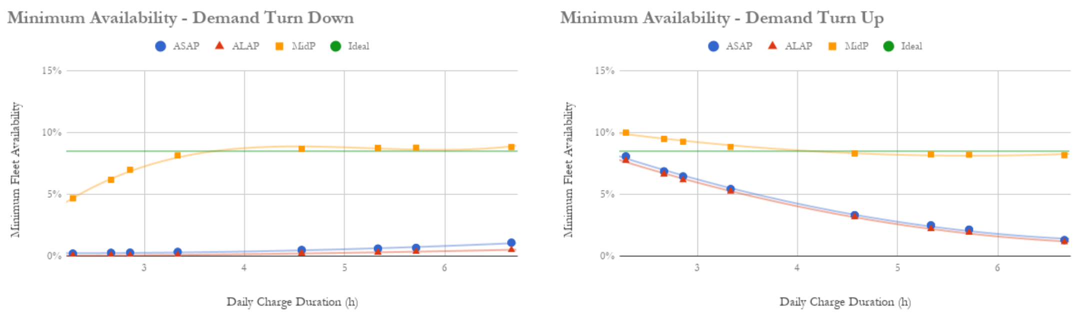


Figure 5.8: Results from Sensitivity Analysis 1.

5.8 Sensitivity Analysis 2

The second sensitivity analysis conducted featured 30 EVs with: 40kWh batteries, 3kW chargers, 90% departure SoC and a linearly spread arrival SoC from 87.5% to 15% inclusively. This produced a more comprehensive distribution of daily charge durations, Figure 5.9. A more definitive relationship was modelled to describe the relationship between fleet availability and charge duration.

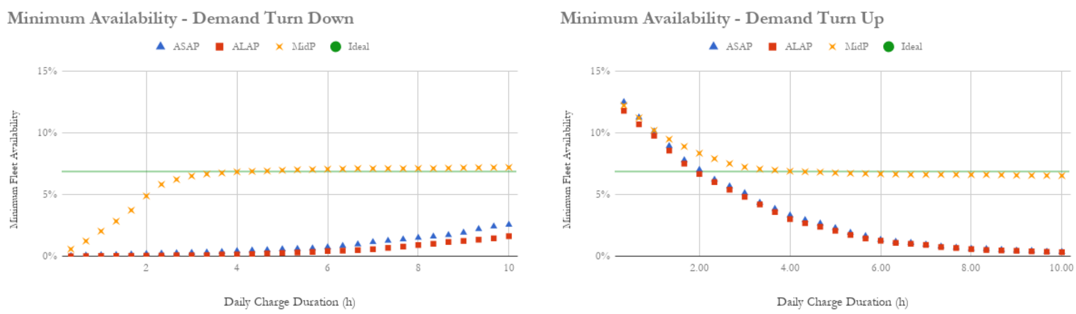


Figure 5.9: Results from Sensitivity Analysis 2.

Both the ASAP and ALAP scheduling methods provided a demand turn down service of below 1% fleet size for charging times below 6 hours rising exponentially to a highest point of 3% at 10 hours. For the midpoint scheduling method, the demand turn down service availability was constant at minimally higher than the ideal value for any charge times greater than or equal to 3.5 hours per day. Any durations less than 3.5 hours tended toward zero linearly.

For the demand turn up services, it was found that all scheduling methods produced a larger than the ideal response for daily charge times smaller than two hours. The ASAP and ALAP methods produced an exponentially decaying function relative to charging time decreasing to below 3% at 5 hours and then further falling to below 1% at 7 hours. This result shows a promising amount of demand turn up availability for EVs that require very little charge daily. The likelihood of the charge time being less than

2 hours is not reflective of the predicted fleet behavioural patterns and would come at the cost of reduced demand turn down potential. The midpoint scheduling method also produced results for demand turn up that were higher than the ideal value for EVs with a daily charge period of fewer than 4 hours from which it followed an exponential decay to ideal availability.

5.8.1 Effect of Charge Duration on Fleet Availability

The results of sensitivity 1 and 2 contained enough data points to be able to design a simple model of the relationships between daily charge duration and minimum fleet availability for the midpoint scheduling model.

The resulting demand turn down response consisted of a two-part model, Equation 5.4 with a linear progression while charge duration is below the cut-off time and then a constant availability for durations longer than this. The model produced a result with R^2 of 0.968, Figure 5.10.

- $t_{cut-off} = 3.5$ hours
- $P_{ideal} = 8.9\%$

If $(t <= t_{cut-off})$

$$P(t) = P_{ideal} * \frac{t}{t_{cut-off}} \tag{5.4}$$

else

$$P(t) = P_{ideal} \tag{5.5}$$

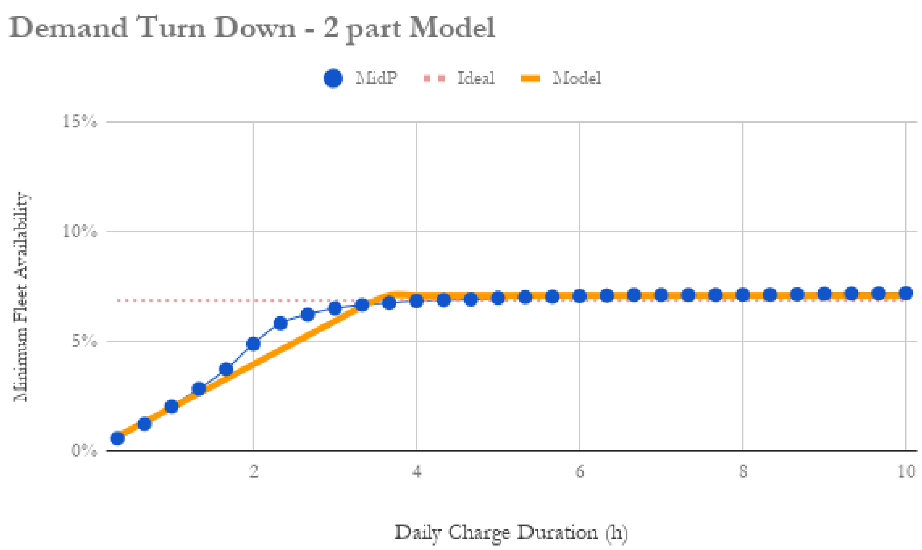


Figure 5.10: Model of Demand Turn Down Response to Charge Duration.

The demand turn up response was modelled as an exponential decay, Equation 5.6. The model produced a result with R^2 of 0.994, Figure 5.11.

$$P(t) = P_{ideal} + P_{ideal} * (1 - r)^t \tag{5.6}$$

For this response the cut-off time, power factor and decay rate are:

- $t_{cut-off}$ = 3.5 hours
- P_{ideal} = 8.1%
- r = 0.9

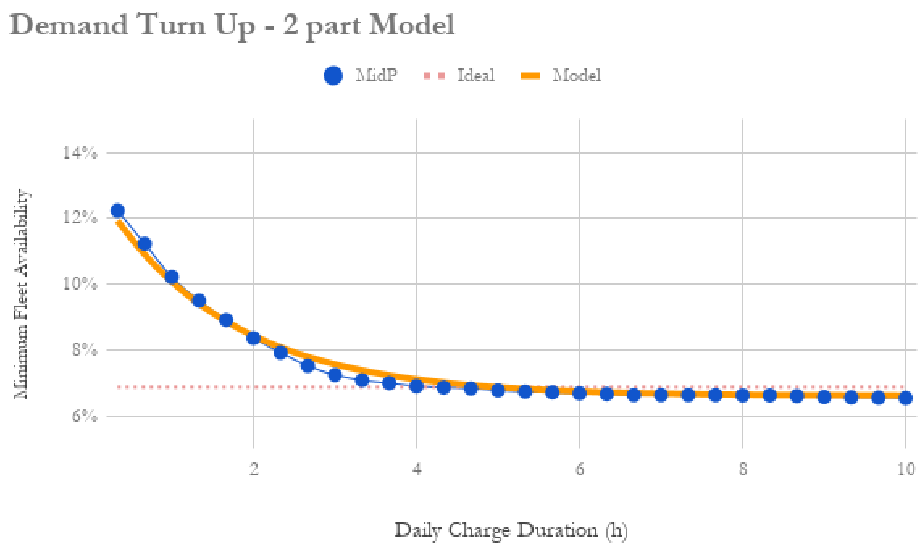


Figure 5.11: Model of Demand Turn Up Response to Charge Duration.

5.9 Sensitivity Analysis 3

To fully understand the results, it is necessary to establish what input parameters affect the cut-off time and ideal power response. To do this, an additional sensitivity was run with the same input criteria as in sensitivity analysis 2. Using a variation in the definition of fleet arrival times to see the effect that higher and lower mean stays had on availability and power response.

By changing the mean arrival times, the number of vehicles present for any given hour adjusted the ideal power threshold. This impacted the resulting model through a difference in P_{ideal} and $t_{cut-off}$, Figure 5.12 and 5.13. The results show that the fleets still maintain a similar relationship between fleet availability and charge duration and just a shifted different cut-off time and ideal power level. In all cases the power was reduced with an increase in mean arrival time as the number of vehicles present at the worst time of day is reduced (approx. 14:00 depending on arrival time).

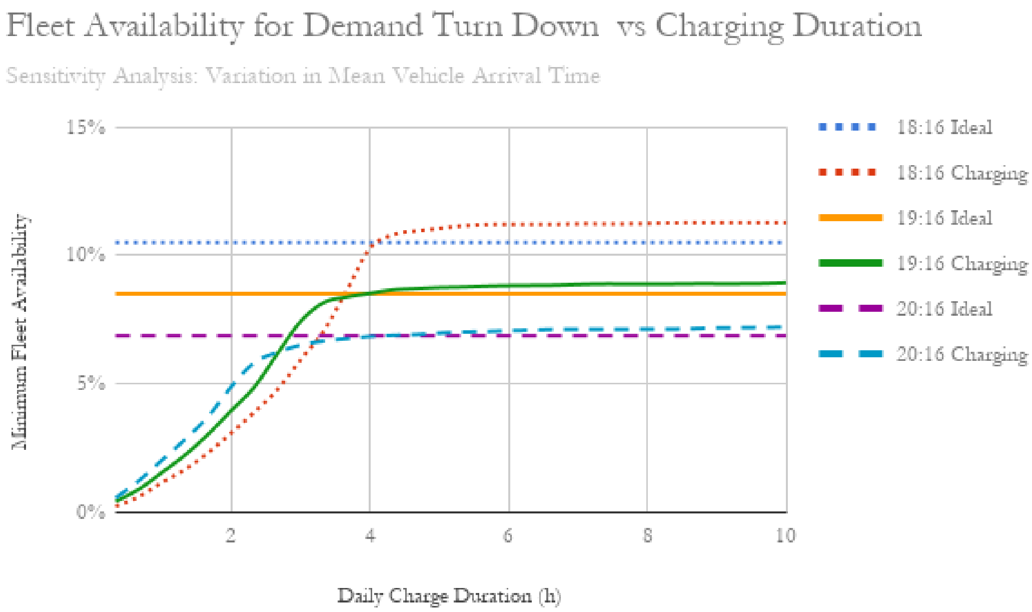


Figure 5.12: Demand Turn Down Response to Variation in Mean Arrival Time.

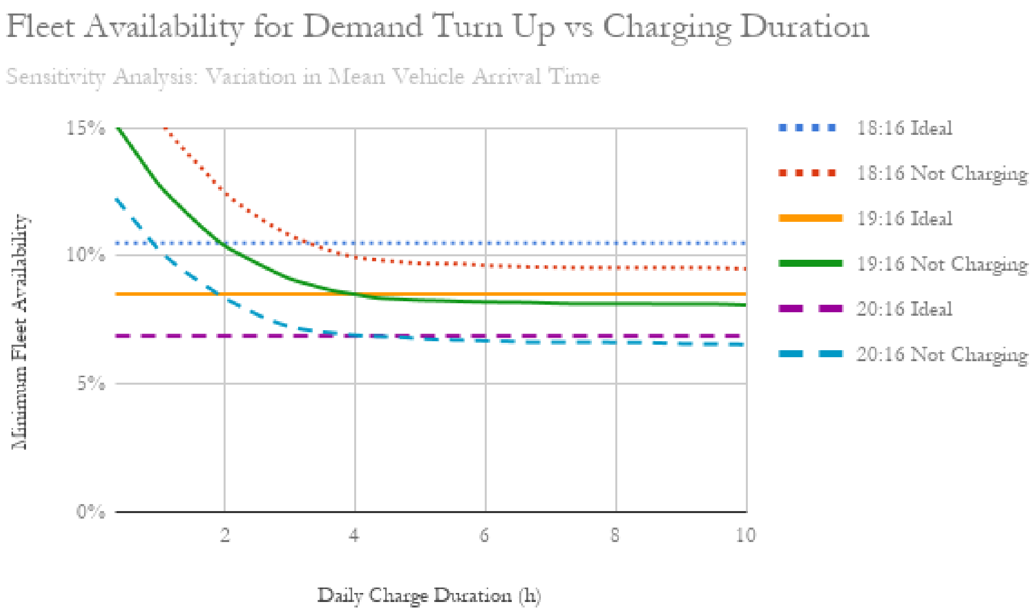


Figure 5.13: Demand Turn Up Response to Variation in Mean Arrival Time.

5.10 Review of Results

The ASAP and ALAP simulations were both far from being ideal, producing availabilities of demand turn up and down significantly below 5% for any vehicle daily charging of more than 4 hours. The midpoint scheduling method achieved a stable fleet availability of within 0.5% of the ideal for both DSR services when vehicle charge times were above 4 hours. This result has meant that to estimate the fleet size required to provide 1MW of DSR the only determining factors are the daily charge time and charging power of the vehicles. The fleet size can be calculated using Equation 5.7 with results conditional on the daily charge duration being greater than 4 hours, Table 5.6.

$$N(P_{DSR}) = \frac{P_{DSR}}{P_{EV} * \eta} \tag{5.7}$$

P_{DSR} is the required power for the DSR turn up or turn down. P_{EV} is the charging power per EV $/eta$ Is the ideal availability (half of the minimum fleet availability at home during the day)

Table 5.6: Fleet Size Requirements using Midpoint Scheduling

DSR Contracted Power	**EV Charging Power**	**Fleet Size Required**
1MW	3kW	4167
1MW	7kW	1786
3MW	3kW	12500
3MW	7kW	5357
5MW	3kW	20833
5MW	7kW	8929

6 Unidirectional vs V2G

As discussed in section 2.1 the potential of using vehicles with bi-directional (V2G) capabilities further increase the fleet's potential for grid support services by allowing the transfer of power into the grid and not simply the reduction in power out. In order to quantify the extent to which the power response is increased using bi-directional power electronics, the system architecture was changed to enable 2 additional states of vehicle charge status. The states possible are shown in Table 6.1 below wherein the response to a demand turn down call the vehicles are able to generate the equivalent power to the amount they normally consume during charging.

Table 6.1: Vehicle States for V2G Capable Fleet.

State	**Normal Vehicle Activity**	**DSR Direction**	**New Vehicle Activity**	**Factor of Change in Demand**
0	Vehicle not at Home			0
1	Charging	No - DSR	Charging	0
2	Not Charging		Not Charging	0
3	Charging	Demand Turn Down	**Generating**	2
4	Not Charging		**Generating**	1
5	Charging	Demand Turn Up	Charging	0
6	Not Charging		Charging	-1

With the use of the new states and the demand change factors it was possible to adapt the algorithm without changing the overall structure or priority functions. The total fleet power and DSR power change were calculated then using the equations Equation 6.1 and Equation 6.2 respectively

$$P_{Demand} = P_{EV} * \left[2 * \sum_{i=1}^{N} \Big\{ if State = [1,5,6] \Big\} - \sum_{i=1}^{N} \Big\{ if State = [3,4] \Big\} \right] \tag{6.1}$$

$$P_{Demand} = P_{EV} * \left[2 * \sum_{i=1}^{N} \Big\{ if State = [3] \Big\} + \sum_{i=1}^{N} \Big\{ if State = [4] \Big\} - \sum_{i=1}^{N} \Big\{ if State = [6] \Big\} \right] \tag{6.2}$$

The sensitivity analyses were rerun on the newly modified algorithm and produced no outlying results indicating correct functionality. After the sensitivities, simulations were run on both unidirectional and V2G systems to produce comparable results. Additional testing was conducted on random vehicles where their SoC was recorded throughout the test and evaluated afterwards to check the charging state during DSR calls and aid debugging.

The following conditions were assumed during simulations:

- Fleet Size: 5 000
- DSR Duration: 1hr
- DSR Occurrence: simulated for every hour of the day
- EV Battery Size: 40kWh
- EV Charge Rate: 3kW (constant, no ramping)
- Arrival time: normal distribution; mean 19.62; standard deviation 3.62
- Departure time: normal distribution; mean 10.53; standard deviation: 3.26
- Arrival SoC: 50%
- Required SoC on departure: 90%

The simulations were run initially with no services called and then both a demand turn up and demand turn down service triggered. To best illustrate the effect DSR activation has on the power demand of the fleet the simulation results have been plotted for the best and worst case scenarios (02:00 and 14:00, figures 6.2 - 6.5) with the normal system response to no DSR services shown in Figure 6.1.

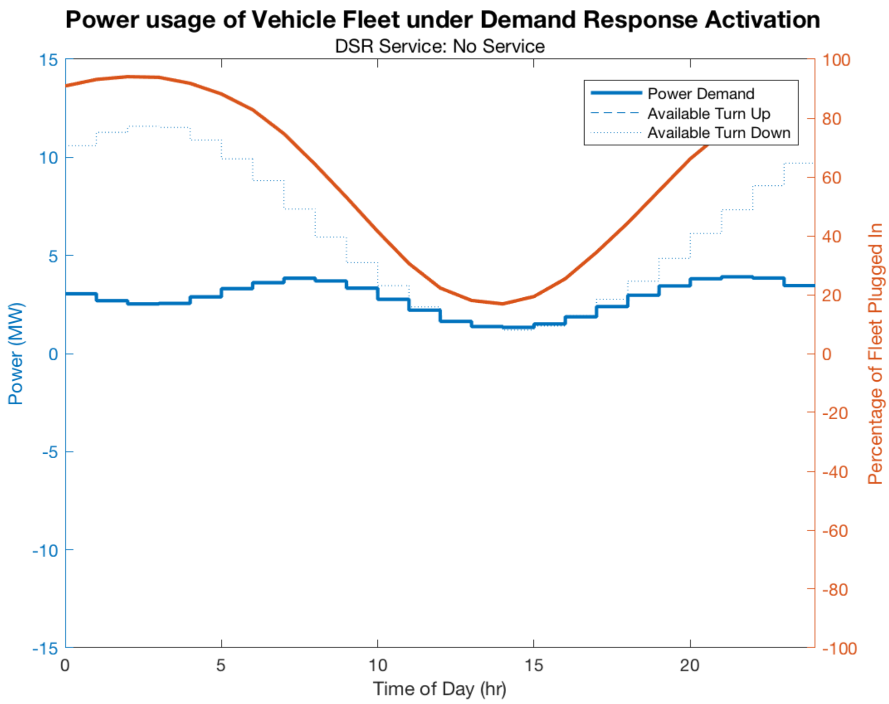
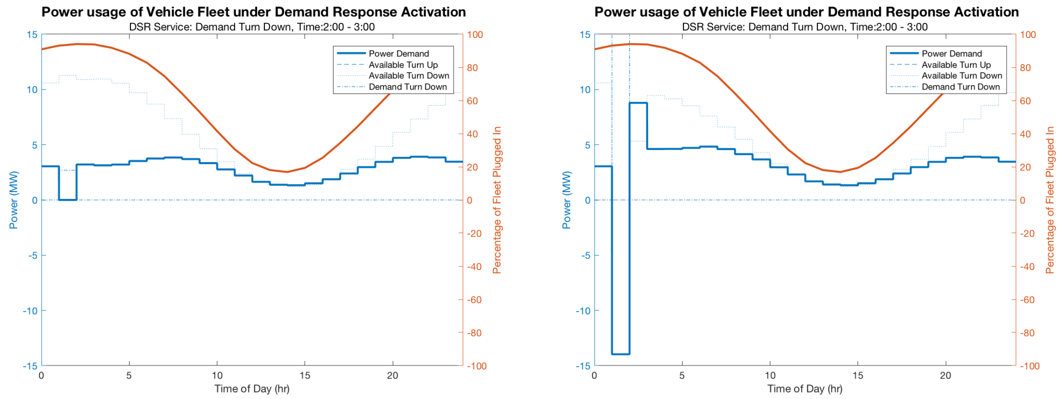


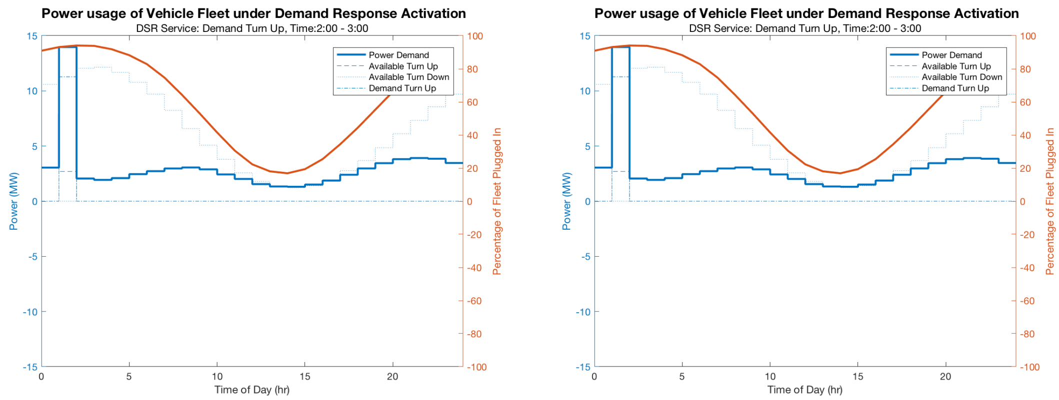
Figure 6.1: Fleet Power Response without DSR service.

6.1 Best Case Scenario



(a) Unidirectional Chargers (b) Bidirectional Chargers

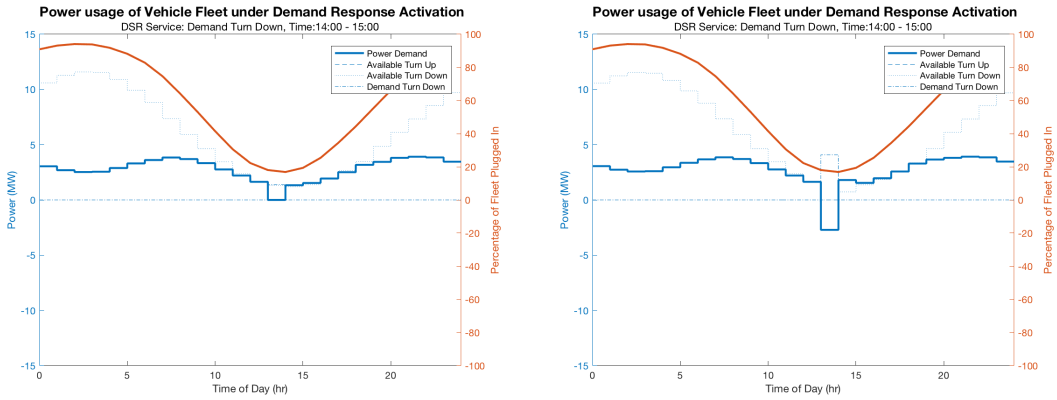
Figure 6.2: Demand Turn Down response to 02:00 activation.



(a) Unidirectional Chargers (b) Bidirectional Chargers

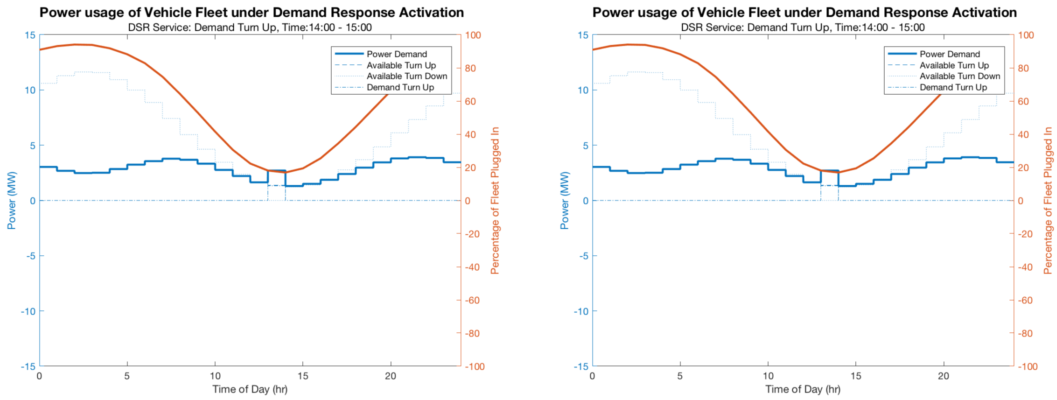
Figure 6.3: Demand Turn Up response to 02:00 activation.

6.2 Worst Case Scenario



(a) Unidirectional Chargers (b) Bidirectional Chargers

Figure 6.4: Demand Turn Down response to 14:00 activation.



(a) Unidirectional Chargers (b) Bidirectional Chargers

Figure 6.5: Demand Turn Up response to 14:00 activation.

6.3 Comparison of DSR Power Response

The resulting DSR availability throughout the day can be seen in Figure 6-6 where the demand turn up response of the two systems produced the exact same result and the demand turn down results considerable larger for a V2G capable fleet.

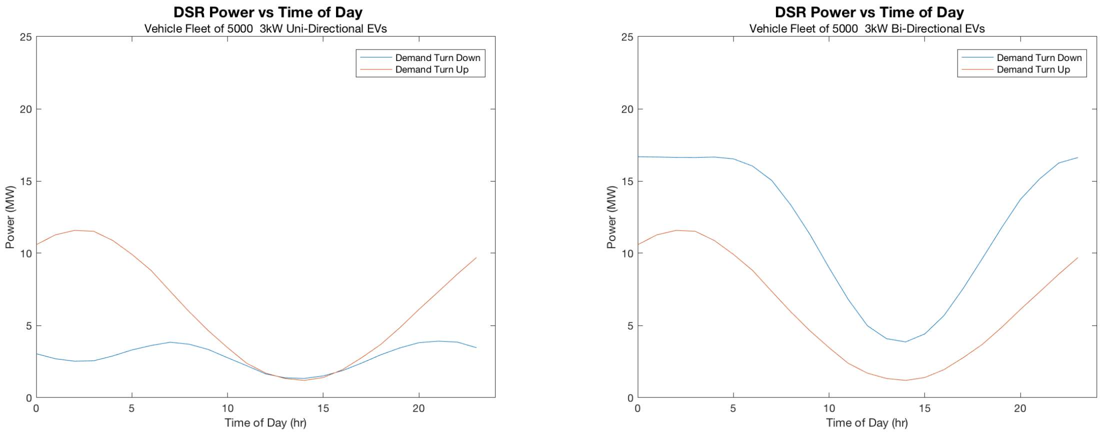


Figure 6.6: Comparison of Uni-directional and Bi-directional systems DSR Availability.

From these results, it was possible to determine an improvement factor achieved through using V2G chargers opposed to uni-directional ones. The demand turn up response was identical in unidirectional and V2G due to a fleet not being able to achieve a larger turn up power demand than the current vehicles charging to the total vehicles plugged in. The number of vehicles charging normally and the driver habits are the same causing the net difference achieved through demand turn up to be the same and thus produce a unity correction factor between unidirectional and bi-directional capable fleets.

$$k_{TurnUp} = \frac{P_{V2G-TurnUp}}{P_{Uni-TurnUp}} = 1 \tag{6.3}$$

The results from the demand turn down system comparisons was largely different with the V2G providing at maximum 7.3 times the power response as uni-directional chargers. This improvement factor, is not constant with the worst case providing 2.9, best case 7.3 and mean 4.3, Figure 6.7.

$$k_{TurnUp} = \frac{P_{V2G-TurnDown}}{P_{Uni-TurnDown}} = \frac{2 * P_{Uni-TurnDown} + P_{Uni-TurnUp}}{P_{Uni-TurnDown}} \tag{6.4}$$

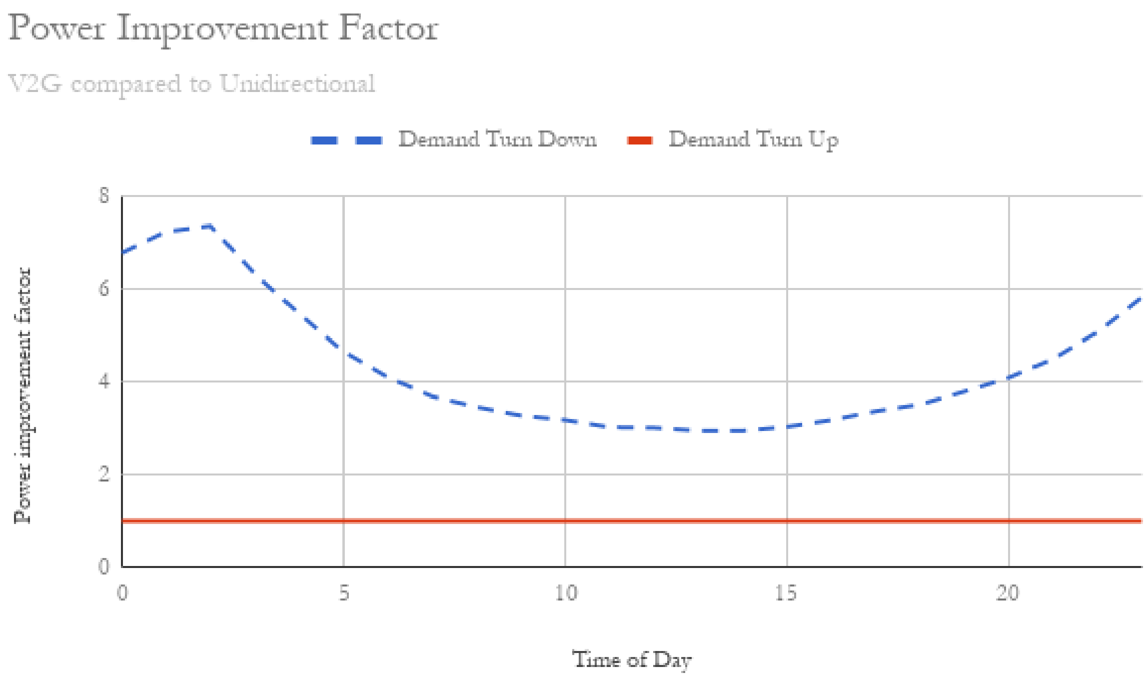


Figure 6.7: Power Improvement Factor response to time of day.

7 Conclusions

This research aimed to explore the technical and economic feasibility of using a fleet of unidirectional vehicles in the place of a V2G fleet for demand response aggregations. Conventional technologies used in balancing services, had slower response times and higher running costs when compared to a fleet of vehicles. Large scale battery storage was able to produce faster response times but, like V2G, the round trip losses increased running costs relative to a unidirectional fleet. A full economic validation was not completed to comparing unidirectional fleet aggregation with the current ancillary market as biding prices were not available.

As a preparation for the construction of a machine learning algorithm the users were profiled to produce groups that would better reflect their driving behaviours than an average based system. These profiles ranged largely based on users' age, gender and vehicle ownership but were not able to be implemented into a training module. The setback of not receiving training data from JLR to train the machine learning algorithm meant that these profiles could never be confirmed, nor needed to be and as such the machine learning algorithm was not developed.

The collection of other datasets proved troublesome with results varying hugely for the same characteristics across sources and samples. These datasets combined were used as a basis for the assumptions in the simulation of the virtual fleet and were re-evaluated through multiple sensitivity analyses to show a stable fleet availability for charging durations larger than 4 hours.

The simulation of the fleet allowed a simple scheduling algorithm to be implemented and the resulting power responses evaluated. The ASAP and ALAP algorithms as expected produced periods of extremely low availability. An unexpected result of the combination of the two produced the MidP algorithm resulting in a stable availability response. This response removed the need for a more complex scheduling algorithm, provided the charge duration was above 4 hours, and was tested through various sensitivities. Using arrival and departure time distributions from [9], the demand turn down and up availabilities were 8.8% and 8.3% compared to the ideal value of 8.5%. This meant that with a fleet of 5000 aggregated Nissan Leafs the MidP scheduling was able to offer 1.42MW turn down and 1.35MW turn up response at the worst time of day.

The final adjustments to the simulations to adapt for a V2G enabled fleet showed that the demand turn up availability was identical to the original fleet. Demand turn down was greater for a V2G fleet by a varying factor between 3.9 and 7.3 dependant on time of day with a mean improvement factor of 4.3. For a 24 hour a day availability service, this proved that with 3.9 times the fleet size, the same service was able to be offered without the need for bidirectional chargers. This result was the most significant result of the project that with additional time could have been used to form an economic comparison between payback period of home chargers. The first public V2G chargers are still to be released, once released it will be possible to develop a complete business case to discuss the potential savings of users and revenue models.

The initial aims planned to develop a complex machine learning algorithm that would treat users individually and then prioritise vehicles dependant on a multivariate priority formula. The resulting algorithm simply charged half the vehicles on arrival and half as late as possible but achieved near ideal fleet availability. This result reflects the misdirection of most research in which complex bidirectional system was developed to use the newest available technology instead of the simpler unidirectional system would produce the same result.

8 Recommendations for Future Work

The most significant failing in this work was the quality and validation of data sources. In future work, the collection of an appropriately sized sample and comprehensive value set is encouraged to allow for more detailed analytics into driving behaviours. The assumptions used in the fleet synthesis were validated through sensitivity analyses, but this could be greatly improved with additional sensitivities conducted to test any of the following areas.

- Vehicle Specifications
  - Fleet composition using different vehicles (PHEV, BEV, Large, Small)
  - Charging power dependency on SoC
  - Vehicle charging at work
- Driver Behaviours
  - Other distributions in arrival and departure times
  - Distribution of daily energy usage
  - Behavioural patterns on weekends
  - Rental Vehicle Fleets
  - Commercial Vehicle fleets
  - Energy usage, in severe weather
  - Energy usage, with seasonal variance
- Power Flow Analysis
  - Non unity power flow
  - Physical testing of response time (design of IoT frequency trigger to allow dynamic FFR)
  - Validation of power response for SO measurement
  - Duration of DSR service
  - Recovery time between DSR triggers

Once the scheduling method has been further tested, it would be recommended to do a business model canvas evaluating different modes of implementation. Possible methods to explore are OEM aggregation with built-in control, or commercial aggregation using OBD control (custom build or API inclusion). A system utilising the OBD port on a vehicle is recommended as the same hardware could be used to collect data on EV users in the validation stage, then through an over the air update, the vehicles would be capable of remote activation. A system that uses OBD port access has the advantage of being scalable across different automotive manufacturers but does come at the inconvenience to the user of not using the default vehicle smart-phone application.

An algorithm capable of learning behaviours was not developed and as such this allows room for further work, however, this is not recommended for the scheduling control. A machine model could be implemented to predict departure times of users and is necessary to allow automatic control and remove human error of drivers predicting departure times.

9 Acknowledgements

The work in this project required large quantities of data and without key components and advisory direction the results would not have been possible. I would like to thank the following people for their guidance and support in data collection.

Dr Sasa Djokic - For the supervision throughout the project and direction to ensure the scope of work attempted was deliverable in the time allocated. Additionally, a large thank you is in order for the lessons that supplemented my general knowledge and grammar skills.

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10 References

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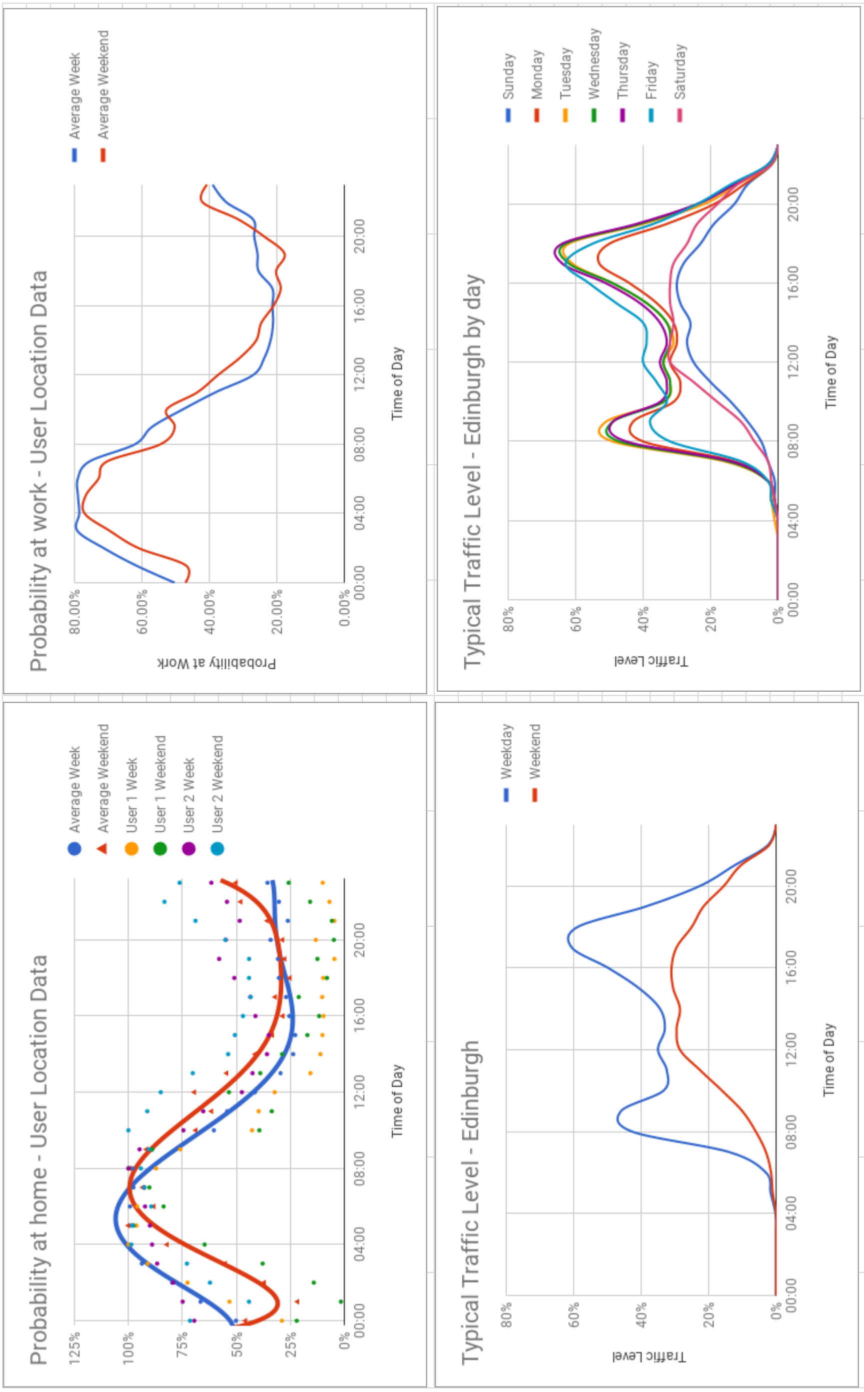
A Appendix A: Collected Data



B Appendix B: Matlab Code (reduced)

```
%%      Title: EV Scheduling Model
%       Author: McDonald, Michael
%       Institution: University of Edinburgh, School of Engineering
%       Package: Matlab 2018b, Academic License
%       Availability: https://github.com/mcdzim/EV_Scheduling_model/
%       License: Open
%       Code version: 1.01
%       Date: 25/04/2018

%% -------------------------------------------------------------------------------------
%   Functions
%-------------------------------------------------------------------------------------
function void = main(void)
    %Simulation Details
    DSR_duration = 1;
    fleet_Size = 5000;
    ChargeRate = 3;
    StartSoC = 0.5;
    Req_SoC = 0.9;
    BatSize = 40;
    results_hours = linspace(0,23,24);
    save_img = 1;
    sim_details = [DSR_duration, fleet_Size, ChargeRate, BatSize, StartSoC, Req_SoC, ...
        save_img];


    % Run Uni-directional Analysis
        Uni_Directional = DSR_Analyse(sim_details);
        'DSR Complete'
        toc;



    % Run Bi-directional Analysis
        V2G_Analyse;
        'V2G Complete'
        toc;

    % %Run Sensitivity Analysis
        Sensitivity_Analysis;
        'Sensitivity Analysis'
        toc;
end


```

```
%% -------------------------------------------------------------------------------------
%   DSR Charging with uni-diectional chargers
%-------------------------------------------------------------------------------------
function result = DSR_Charge(DSR_specs)
    %%Function Details
    % DSR_hour is the hour the service is called upon
    % DSR_direction is the service required: 0= no service, 1= turn down, 2=turn up
    % DSR_duration is the time service is needed for

    %Result is in the format of 24:8 with vehicles states for hours of day
    %Result(:, 1) = Hour of Day
    %Result(:, 2) = Number of Vehicles: At Home
    %Result(:, 3) = Number of Vehicles: Charging
    %Result(:, 4) = Number of Vehicles: Not Charging
    %Result(:, 5) = Number of Vehicles: Were Charging, Now Demand Turn Down
    %Result(:, 6) = Number of Vehicles: Were Not Charging, Now Demand Turn Down     - N/A
    %Result(:, 7) = Number of Vehicles: Were Charging, Now Demand Turn Up           - N/A
    %Result(:, 8) = Number of Vehicles: Were Not Charging, Now Demand Turn Up
    %-------------------------------------------------------------------------------------

    %% Fleet Definitions

    %% Calculate 1/2 of fleet using ASAP Priority

    %% Calculate 1/2 of fleet using ALAP Priority

    %% Record Results for export

    %%  Display Results
end
```

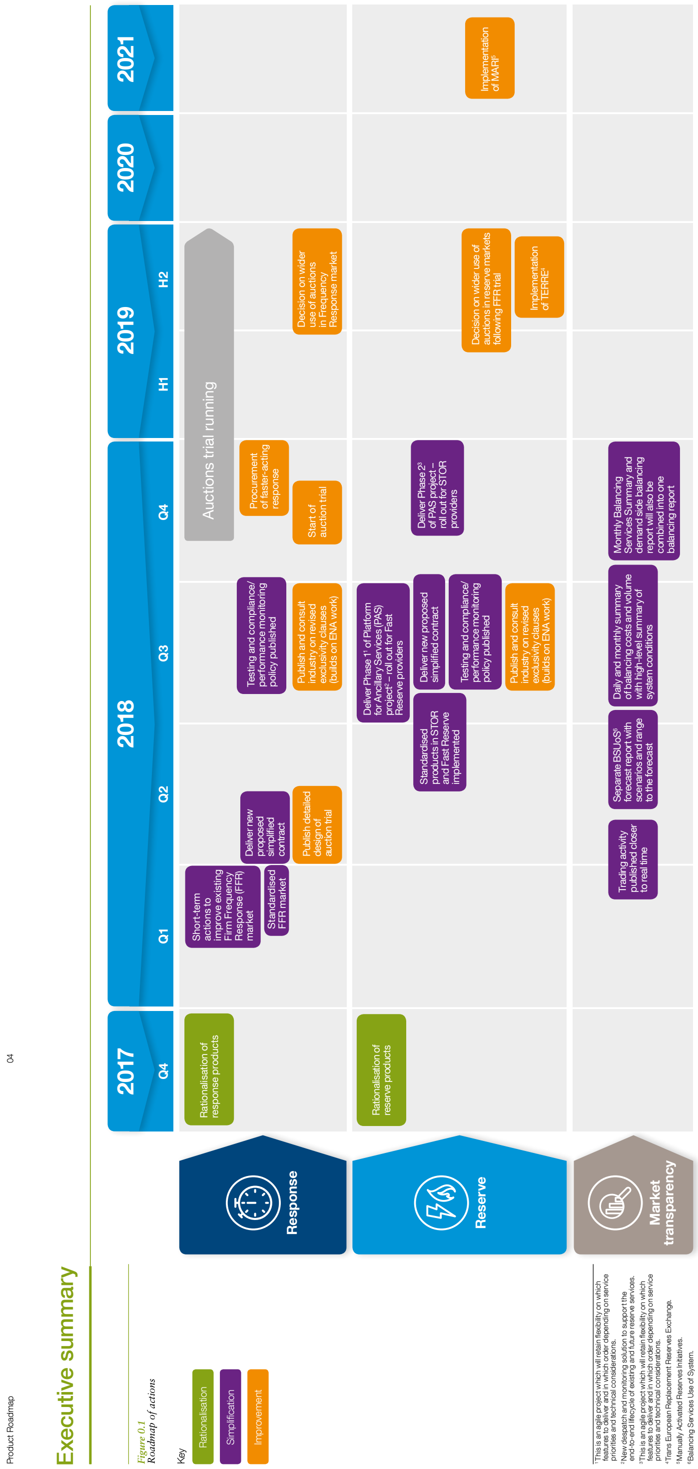
```
function result = DSR_Analyse(input_criteria)
    %Date Created: 14-04-2018
    %Date last edited: 15-04-2018
    %% Simulation Details
    %input_criteria = [DSR_duration, fleet_Size, ChargeRate, BatSize, StartSoC, ...
        Req_SoC, save_img]

    % result is returns 2:24 array
    % result(1, :) = Demand turn Down response for 24 hours
    % result(2, :) = Demand turn Up response for 24 hours
    %--------------------------------------------------------------------------------------
    %% Run Simulation for Demand Turn Down every hour of the day
    DSR_direction = 1;
    for x = 1:24
        DSR_hour = x;
        DSR_details = [DSR_hour, DSR_direction, DSR_duration, ChargeRate, fleet_Size, ...
            StartSoC, Req_SoC, BatSize];
        sim_results = DSR_Charge(DSR_details);

        %sim_results = 24:8
        %sim_results(:, 1) = hour of day
        %sim_results(:, 2) = Vehicles at Home
        %sim_results(:, 3) = Vehicles Charging     - No DSR
        %sim_results(:, 4) = Vehicles Not Charging - No DSR
        %sim_results(:, 5) = Vehicles was Charging     - Now Not Charging
        %sim_results(:, 6) = Vehicles was Not Charging - Now Not Charging   --- This is ...
            a useless state but left in to keep symmetry
        %sim_results(:, 7) = Vehicles was Charging     - Now Charging       --- This is ...
            a useless state but left in to keep symmetry
        %sim_results(:, 8) = Vehicles was Not Charging - Now Charging

        %% Save Results
    end

    %% Run Simulation for Demand Turn Up every hour of the day
    DSR_direction = 2;
    for x = 1:24
    end

    %% Run Simulation for No Service once
    DSR_direction = 0;
    for x = 1:1
    end

    %% Save Results
    temp_result(1, :) = results_DTD;
    temp_result(2, :) = results_DTU;
    result = temp_result
end
```

```
%% ------------------------------------------------------------------------------------------
%   DSR Charging with bi-diectional chargers (V2G)
%-----------------------------------------------------------------------------------------
function result = V2G_Charge(DSR_specs)
    %%Function Details
    % DSR_hour is the hour the service is called upon
    % DSR_direction is the service required: 0= no service, 1= turn down, 2=turn up
    % DSR_duration is the time service is needed for

    %Result is in the format of 24:8 with vehicles states for hours of day
    %Result(:, 1) = Hour of Day
    %Result(:, 2) = Number of Vehicles: At Home
    %Result(:, 3) = Number of Vehicles: Charging
    %Result(:, 4) = Number of Vehicles: Not Charging
    %Result(:, 5) = Number of Vehicles: Were Charging, Now Generating
    %Result(:, 6) = Number of Vehicles: Were Not Charging, Now Generating   - N/A
    %Result(:, 7) = Number of Vehicles: Were Charging, Now Demand Turn Up          - N/A
    %Result(:, 8) = Number of Vehicles: Were Not Charging, Now Demand Turn Up
    %------------------------------------------------------------------------------------------

    %% Fleet Definitions
    %% Calculate 1/2 of fleet using ASAP Priority
    %% Calculate 1/2 of fleet using ALAP Priority
    %% Record Results for export
    %%  Display Results
    %% Record Results for export
    for x_hour = 1:24
        %Hour of Day
        temp_result(x_hour, 1) = x_hour-1;
        %Vehicles at Home
        temp_result(x_hour, 2) = fleet_Size - sum(FleetCharging(x_hour, :)==0);
        %Vehicles Charging
        temp_result(x_hour, 3) = sum(FleetCharging(x_hour, :) == 1);
        %Vehicles Not Charging
        temp_result(x_hour, 4) = sum(FleetCharging(x_hour, :) == 2);
        %Vehicles was Charging - Now Injecting
        temp_result(x_hour, 5) = sum(FleetCharging(x_hour, :) == 3);
        %Vehicles was Not Charging - Now Injecting
        temp_result(x_hour, 6) = sum(FleetCharging(x_hour, :) == 4);
        %Vehicles was Charging - Now Charging
        temp_result(x_hour, 7) = sum(FleetCharging(x_hour, :) == 5);
        %Vehicles was Not Charging - Now Charging
        temp_result(x_hour, 8) = sum(FleetCharging(x_hour, :) == 6);
    end
    result = temp_result;

end
```

```matlab
function result = V2G_Analyse(input_criteria)
    %%Function Details
    %Run simulation for every hour of day
    %Date Created: 14-04-2018
    %Date last edited: 15-04-2018
    %% Simulation Details
    %input_criteria = [DSR_duration, fleet_Size, ChargeRate, BatSize, StartSoC, ...
        Req_SoC, save_img]

    % result is returns 2:24 array
    % result(1, :) = Demand turn Down response for 24 hours
    % result(2, :) = Demand turn Up response for 24 hours
    %-----------------------------------------------------------------------------------

    %% Run Simulation for Demand Turn Down every hour of the day
    DSR_direction = 1;
    for x = 1:24
        DSR_hour = x;
        DSR_details = [DSR_hour, DSR_direction, DSR_duration, ChargeRate, fleet_Size, ...
            StartSoC, Req_SoC, BatSize];
        sim_results = V2G_Charge(DSR_details);

        %sim_results = 24:8
        %sim_results(:, 1) = hour of day
        %sim_results(:, 2) = Vehicles at Home
        %sim_results(:, 3) = Vehicles Charging     - No DSR
        %sim_results(:, 4) = Vehicles Not Charging - No DSR
        %sim_results(:, 5) = Vehicles was Charging     - Now Injecting
        %sim_results(:, 6) = Vehicles was Not Charging - Now Injecting
        %sim_results(:, 7) = Vehicles was Charging     - Now Charging    --- This is a ...
            useless state but left in to keep symmetry
        %sim_results(:, 8) = Vehicles was Not Charging - Now Charging

        %Power Demand = Charging[3,7,8] - Injecting[5,6]

        %% Save Results
    end

    %% Run Simulation for Demand Turn Up every hour of the day
    DSR_direction = 2;
    for x = 1:24
    end

    %% Run Simulation for No Service
    DSR_direction = 0;
    for x = 1:1
    end
end
```

```
%% ------------------------------------------------------------------------------------
%   Charging Methods
%-------------------------------------------------------------------------------------

function result = ChargingModel(fleet_def)

function void = Sensitivity_Analysis(void)

function fleet_state = Charge_ASAP(fleet_data)

function fleet_state = Charge_ALAP(fleet_data)

function fleet_state = Charge_MidP(fleet_data)

function new_fleet_data = Vehicle_home(fleet_data, time)
```

C Appendix C: National Grid Reserve Services Roadmap [1]



D Appendix D: Digital Appendix

There is a large quantity of resources unable to be included in print format. These have been saved to an online repository. The address below will provide open access to all files used and developed during this project and the appropriate user manuals to allow further work.

`https://github.com/mcdzim/EV_Scheduling_model/`