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Electric Vehicles with Vehicle-to-Grid Capability in the Future Power System: Optimal Charging, Discharging and Trip Scheduling

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Abstract

As countries electrify road transport and decarbonise electricity, the demand for power is increasing while generation becomes more intermittent due to renewable energy uptake. This makes power system operation challenging and expensive. With expected high electric vehicle load, coordinating charging and discharging to balance supply and demand for electricity is important to avoid overburdening the network. Bidirectional charging through Vehicle-to-Grid could unlock significant storage capacity from parked electric vehicles when they are plugged in.

This thesis focuses on the opportunities presented by scheduling charging, discharging and travel (trips) for commercial electric vehicle fleet operation to benefit both the fleet and network operators. Opportunities for carbon emission reduction are also considered. Throughout, this thesis integrates real-world data and learning from the Vehicle-to-Grid demonstrator project, E-Flex, of which the author was a contributor. The study identifies economically efficient ways in which a future system may operate, and highlights barriers to such implementation.

A foundational optimisation model is set out and an analysis of examined scenarios is produced, covering various configurations for scheduling charging for 12 trial fleets. The multi-service optimal charging scheduling model developed for this analysis is extended in two ways. Firstly, a novel operational strategy integrating trip scheduling is implemented with future energy and ancillary service prices to understand potential scenarios for commercial fleets. Secondly, to account for randomness in prices and travel data, machine learning is applied to a multi-service charging strategy, showing the benefits of real-time scheduling. This approach utilises the rich data-set provided by the real world project and employs a novel reinforcement learning environment.

The thesis contributes to understanding optimal operational strategies for electric vehicles with Vehicle-to-Grid in the future power system, demonstrating the benefits of market participation.

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Alicia Blatiak, January 2023

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Dedication

*To my father, Dr Andrew Blatiak,
from your favourite daughter.*

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Nomenclature

The main notation used throughout the thesis is stated below for quick reference. Other symbols are defined as required throughout the text.

List of Abbreviations

CCC	The Climate Change Committee
CCGT	Combined Cycle Gas Turbine
DC	Dynamic Containment
DNO	Distribution Network Operator
DSO	Distribution System Operator
DSR	Demand Side Response
E-VRP	Electric Vehicle Routing Problem
ESO	Energy System Operator
ETS	Emissions Trading Scheme
EV	Electric Vehicle
FR	Frequency Response
GB	Great Britain

GHG	Greenhouse Gas
IDLES	Integrated Development of Low-carbon Energy Systems
ML	Machine Learning
PFR	Primary Frequency Response
RES	Renewable Energy Sources
SOC	State of Charge
TOU	Time-of-use
TSO	Transmission System Operator
V1G	Smart Charging
V2G	Vehicle-to-Grid
VRP	Vehicle Routing Problem

Nomenclature for Chapter 3

A. Indices and Sets

t	Index of time steps
T^{grid}	Set of time steps that the EV is connected to grid
T	Total set of time steps
i	Index of EVs
I	Set of EVs in fleet

B. Parameters

η_c	Charging efficiency of EV
E^{req}	Energy required upon departure of the EV (kWh)

$P^{c,max}$	Maximum charging power of charger (kW)
$P^{d,max}$	Maximum discharging power of charger (kW)
t_{dep}	Time step of departure of EV
f_0	Nominal frequency of the power grid (Hz)
$E_{t_{start}}$	Battery energy at start of time period T (kWh)
η_d	Discharging efficiency of EV
π_t^b	Hourly import energy (buy) price (£/kWh)
π_t^{BSup}	Hourly upward balancing service price (£/kWh)
π_t^{BSdw}	Hourly downward balancing service price (£/kW/h)
$\pi_t^{CO_2}$	Hourly CO ₂ price (£/kW/h)
$\tau_t^{CO_2}$	Carbon intensity of grid generation (g _{CO2} /kW)
π_t^s	Hourly export energy (sell) price (£/kWh)
E^{max}	Maximum energy limit of EV battery (kWh)
E^{min}	Minimum energy limit of EV battery (kWh)
$E_{t,i}^{tr}$	Energy needed by EV i for travel at time step t (kWh)

C. Variables

$BS_{t,i}^{up}$	Upward balancing service provision by EV i at time step t (kW)
$BS_{t,i}^{dw}$	Downward balancing service provision by EV i at time step t (kW)
$C_{t,i}$	Charging power of EV i at time step t (kW)
$D_{t,i}$	Discharging power of EV i at time step t (kW)
$E_{t,i}$	Energy level of EV i battery at the end of time step t (kWh)

Nomenclature for Chapter 4

A. Indices and Sets

t	Index of time steps
T	Set of total time periods
T^{grid}	Set of time steps that EV is connected to grid
T^{window}	Set of time steps where trips are permissible
T^{trip}	Set of time steps where trip occurs

B. Parameters

E^{min}	Minimum battery capacity (kWh)
E^{start}	Battery energy at start of time period T (kWh)
E^{req}	Battery energy required at end of time period T (kWh)
E^{tr}	Energy needed for travel (kWh)
f_0	Nominal frequency of the power grid (Hz)
Δf_{max}	Lowest nadir admissible to avoid Under-Frequency Load Shedding
H	Total system inertia (MVA $\cdot$ s)
H_{CCGTs}	Inertia from Combined Cycle Gas Turbines (MVA $\cdot$ s)
H_{floor}	Floor for inertia (MVA $\cdot$ s)
P_{infeed}	Largest power infeed in the national system
δ	Penalty term
P^{max}	Maximum power rating of charger (kW)
t_s	Minimum required time that service needs to be sustained for

η_c	Charge efficiency
η_c	Discharge efficiency
π_t^b	Hourly import energy (buy) price (£/kWh)
π^{BSup}	Hourly upward balancing service price (£/kW/h)
π_t^s	Hourly export energy (sell) price (£/kWh)
E^{max}	Maximum battery capacity (kWh)
<i>C. Variables</i>	
t_{start}	Trip start time
$BSup_t^c$	Upward balancing service availability by reducing charging (kW)
$BSup_t^d$	Upward balancing service availability by increasing discharging (kW)
C_t	Charging power at time step t (kW)
D_t	Discharging power at time step t (kW)
E_t	Battery energy at time step t (kWh)
y	Binary variable
x_1	Auxiliary decision variable

Nomenclature for Chapter 5

A. Indices

t	Index of time steps
-----	---------------------

B. Parameters

η_c	Charging efficiency of EV
$P^{c,max}$	Maximum charging power of charger (kW)

$P^{d,max}$	Maximum discharging power of charger (kW)
t_s	Safety period from end of charging session
t_{dep}	Time step of departure of EV
A_t	Binary availability parameter indicating whether the EV is connected to the grid at time step t ($A_t=1$) or not ($A_t=0$)
η_d	Discharging efficiency of EV
π_t	Energy price at time step t (£/kWh)
BS_t^{up}	Upward balancing service price at time step t (£/kW/h)
BS_t^{dw}	Downward balancing service price at time step t (£/kW/h)
E^{max}	Maximum energy limit of EV battery (kWh)
E^{min}	Minimum energy limit of EV battery (kWh)
E_t^{tr}	Energy needed by EV for travel at time step t (kWh)
E^{req}	Energy required upon departure of the EV (kWh)

C. Variables

BS_t^{up}	Upward balancing service provision by EV at time step t (kW)
BS_t^{dw}	Downward balancing service provision by EV at time step t (kW)
C_t	Charging power of EV at time step t (kW)
D_t	Discharging power of EV at time step t (kW)
E_t	Energy level of EV battery at the end of time step t (kWh)

Chapter 1

Introduction

1.1 Context

Given the global agenda to reduce reliance on fossil fuels and reduce pollutants and carbon emissions, the transition from internal combustion engine vehicles to electric vehicles (EVs) is seen as an important one. In 2020, despite the Covid-19 pandemic, a record three million new EVs were registered globally, a 41% increase from the previous year [1]. This brought the total EVs on the road to a 1% stock share of vehicles [2]. By 2030, the global number of EVs on the road is projected to reach 145 million, rising to potentially as much as 230 million, if governments accelerate efforts to reach climate goals [1].

As policies globally drive the development and deployment of low carbon technologies [3], there exist considerable effects on the power system. The integration of renewable energy sources on the generation side of the system is challenging, as they are variable and difficult to control. Utilizing low carbon devices on the demand side is also challenging, given that decarbonizing the heat and transport sectors will potentially increase peak electrical load significantly. There has been a particular focus on the adoption of electric vehicles (EVs) in the decarbonization of the road transport sector and so this load must be carefully considered when making the transition. This additional EV load, if uncoordinated, could lead to a host of issues, including grid problems [4] likely necessitating network investments [5] and difficulties in stable operation

and the reliability of the power system [6].

At the same time as this transition in the road transport sector, the sources of energy generation are changing with the growth of variable renewable energy and inflexible nuclear power. By 2030, energy production costs could be reduced by up to 50%, thanks to a higher penetration of renewable energy [5]. However, the cost of flexibility services (services needed to keep electricity supply and demand balanced) could increase by up to 15 times with respect to current levels [5]. Although market design has historically focused on trading energy as a basic commodity, services needed for stable operation (or balancing services) are still under development and will need to adapt to these fast-changing market conditions.

The markets for energy and balancing services, as well as the emerging carbon market, could provide a framework whereby novel technologies, such as EVs, can be utilised and help to balance the power system [7]. This would have the added benefit of efficiently securing stable system operation (free of black-outs), as well as incentivising off-peak usage or discharging excess energy by end-users of EVs.

The provision of flexibility by EVs is an option that has been proposed in [8] and developed for participation in various markets [9], for example the day ahead electricity market [10] and in frequency response (FR) [11]. Reference [12] provides a review of work done to model EVs participating in such markets, to realise their value to the power system and the EV user. More recently, EV fleets with vehicle-to-grid (V2G) technology have been modelled to bring whole system benefits in [13], taking into consideration the cost but also carbon emission savings of EV deployment.

With many potential benefits identified, the implementation of V2G is not yet widespread, mostly due to the market, regulatory and economic barriers that still exist. For current V2G projects coming online worldwide, [14] is a useful reference. Of the Innovate UK funded projects funded to assess the potential of this technology, E-Flex seeks to demonstrate the value of V2G to fleets in current and future market conditions with real travel data. This is to pinpoint which barriers to market still exist, and what steps need to be taken to overcome them [15]. At the time this work was carried out, the EVs on project E-Flex were the first to have performed

dynamic frequency response in the UK in 2021 [16], and it is with this real data set that the case studies in this thesis are constructed.

1.2 Motivation

The global transport sector accounts for 25% of direct CO₂ emissions from fossil-fuel based combustion. Road vehicles make up the largest proportion of this contribution (almost three quarters) [17]. In the UK, road transport makes up 91% of the total emissions from the transport sector, which is responsible for 27% of the country's total emissions. The energy generation sector accounts for 21% [18]. It is the simultaneous decarbonisation of the transport and energy sectors that poses a huge challenge because the electrification of the road transport sector (i.e. a primary strategy to decarbonise) relies on the energy sector to charge vehicles. The decarbonisation of the energy sector in turn relies on renewable energy, the generation of which is difficult to accurately predict. With energy generation that is hard to predict and a higher demand for energy by electric vehicles, more frequent system imbalances become inevitable. With imbalances come higher costs of energy system operation, as well as network issues, such as blackouts.

Upon closer examination, there exists an opportunity to put mechanisms in place that maximise on the new source of flexibility EVs have to offer. Flexibility, here, depends on the technology:

- Chargers that have uni-directional power flow from the source to the electric vehicle are commonly referred to (and referred to in this thesis) as Grid-to-Vehicle (G2V), smart chargers, or V1G chargers. Here, their flexibility comes from the ability to control the timing of the charging and the power level at which the charging is performed.
- Chargers that have bi-directional power flow and can charge the vehicle as well as discharge the vehicle are commonly referred to as Vehicle-to-Grid (V2G) or, more recently, Vehicle-to-Everything (V2X) chargers. In this thesis, they are referred to as V2G chargers, and their flexibility comes from the ability to control the timing of their charging and

discharging timing, as well as charging and discharging power levels.

This flexibility could allow for a higher level of renewable energy for the power system in Great Britain, creating a win-win scenario; the electrification of road transport will reduce direct emissions from vehicles, while more renewable energy will reduce the emissions from the energy sector. In order to make this solution feasible and sustainable, appropriate financial incentives need to be in place to encourage the utilisation of flexibility from EVs. Research into incentives for EVs is very important moving forward, while there exists a gap concerning this issue in the literature. This includes the need to quantify potential revenues for EV users under current and future scenarios, investigate optimal EV operation to maximise revenues and address the uncertainties in such operation coming from unpredictable travel patterns and prices. Once it is financially beneficial and practical for EVs to offer their flexibility through relevant market mechanisms and operational strategies, the road transport sector's decarbonisation and the energy system's decarbonisation can happen in a more synchronised and effective way.

This thesis seeks to investigate this potential role that EVs could play in the simultaneous decarbonisation of road transport and energy, and to address gaps identified in the literature. An EV fleet operator's perspective is chosen because at an aggregated level (of, e.g. hundreds of vehicles), more coordination and scale is achievable, allowing for more impact at the energy system level. Hence, this thesis presents research into commercial EV fleet operation with Vehicle-to-Grid (V2G) technology in the current and future power system. It provides insights into which strategies commercial EV fleets can take in order to put this win-win scenario in action. By modelling charging, discharging and travel (or trip) schedules using real-world data, the potential of EV fleets in the future electricity system in GB is investigated. This is done by quantifying revenues of different operational scenarios for EV fleet operators using optimisation, and then by proposing real-time optimal control of fleet charging and discharging using machine learning. The latter is an application that brings several significant benefits to EV charging and discharging operation, offering a practical way to implement this work in the real world.

1.3 Research Questions

In order to investigate the role of EVs in decarbonising the road transport and energy sectors, coordinating when EVs charge (and discharging where discharging is feasible) needs to be carefully considered and modelled. It is this timing that - through market mechanisms - will yield financial rewards. To evaluate the different strategies for revenue generation for commercial EV fleets given current market conditions, the following core research question is answered in Chapters 3 and 4 using optimisation:

What are the optimum charging, discharging and travel (trip) schedules to maximise revenues for EV fleet operators?

As the GB power system incorporates more renewable energy, its inertia, meaning the physical inertia of rotating masses in thermal plants (further described in Section 2.3.1 of Chapter 2), will decrease. This will have an impact on energy and balancing service prices, which in turn will affect the revenues and charging strategies of EV fleet operators. To investigate these effects, the next question this thesis seeks to answer in Chapter 4 is:

How will these schedules likely change in a low-inertia system in the future?

With a view to explore the potential for further integration of EVs into the power system, the next question lies at the intersection of electrical engineering and transport studies. In Chapter 4, the following question is also answered:

What will the value of simultaneously scheduling both EV charging and trips be in the future power system?

Lastly, the uncertainties around travel patterns and service market prices will need to be taken into consideration for the real world application of these charging schedules. A novel, data-driven machine learning approach to solving this problem is proposed in Chapter 5, addressing the following question:

How can fleet operators account for uncertainty in travel patterns and service prices to schedule

EV charging and discharging with V2G in real-time using machine learning?

1.4 Thesis Structure and Original Contributions

This thesis is structured as follows:

- **Chapter 2** provides a background to the need for flexibility as various sectors are decarbonised. It gives details of the markets already in place, and ones that are emerging, to manage this transition. These include the energy market, Transmission System Operator (TSO) service market, Distribution System Operator (DSO) services market, and the carbon market.
- **Chapter 3** presents a foundational mathematical framework, along with a set of examined scenarios, from which the rest of the thesis is built or expanded on. Detailed results of examined scenarios for charging strategies for multiple real-world commercial EV fleets are presented and analysed. The contributions of this chapter are:
 - Accurate characterisation of flexibility of commercial EV fleets participating in ancillary service markets, using real world data from a V2G demonstration project in the UK; and
 - Comprehensive assessment of revenues of commercial V1G and V2G fleets considering present GB scenario with a carbon price sensitivity analysis.
- The foundational models are expanded on in **Chapter 4** to incorporate travel (trip) scheduling in a current and future market scenario. Future summer and winter conditions are modelled, including projected higher renewable uptake, to understand the future role of EVs with V1G and V2G capability. This chapter forms the basis of work that has been published in [19]. Contributions of this chapter include:
 - Novel scheduling approach for EV fleet operators that includes both charging and trip times, generating additional revenues and exploiting synergies between the power system and road transport system;

- Quantification of the value of scheduling optimal journey times accounting for frequency response prices, limiting battery degradation and accurately capturing provision both from reducing charging and increasing discharging;
 - Accurate characterisation of flexibility of commercial EV fleets (i.e. hundreds of EVs) participating in ancillary service markets, inferred from real world data from a V2G demonstration project in the UK; and
 - Comprehensive assessment of revenues of commercial V2G fleets considering present and future GB scenarios with various sensitivities, including societal benefits in terms of carbon emissions avoided.
- In order to investigate real-time charging scheduling and address the issue of uncertainties in travel patterns and prices, state of the art Machine Learning (ML) is applied to the EV charging scheduling problem in **Chapter 5**. The contributions of this chapter are:
 - The energy and balancing services provision scheduling problem of an EV with V1G and V2G capability formulated as a Markov decision process (MDP), which does not require knowledge of the EVs’ physical operating models and technical parameters, and factors uncertainties associated with traveling patterns and market prices;
 - A novel Deep RL method to address the formulated problem, namely Proximal Policy Optimisation (PPO), which allows for continuous state and action spaces, has high sampling efficiency (reflected in a fast training process), and ease of implementation;
 - In contrast to previous works using synthetic data for EV travel patterns (usually based on normal distributions around expected values), use of real-world commercial EV fleet data from the E-Flex demonstration project to train and test the examined learning methodologies; and
 - Case studies employing this real-world data to demonstrate the advantages of the proposed approach over other state-of-the-art methods (Deep Q-Network and Deep Deterministic Policy Gradient).

The work in this chapter is to be submitted to the Sustainable Energy, Grids and Networks journal.

- Conclusions and future work are discussed in **Chapter 6**.
- A sample of the raw EV data used throughout is included in **Appendix A**.
- Detailed and extended results from the nine fleets not included in Chapter 3 are shown in **Appendix B**.

1.5 Publications and Presentations

1.5.1 Journal Papers

A. Blatiak, F. Bellizio, L. Badesa & G. Strbac. Value of Optimal Trip and Charging Scheduling of Commercial Electric Vehicle Fleets with Vehicle-to-Grid in Future Low Inertia Systems. *Sustainable Energy, Grids and Networks*, May 2022 [19]

A. Blatiak, D. Qiu, D. Papadaskalopoulos & G. Strbac. Multi-Service Real-Time Scheduling of Commercial Electric Vehicle Fleet with V2G Using Deep Reinforcement Learning. *To be submitted to Sustainable Energy, Grids and Networks Journal*

1.5.2 Relevant Presentations

A. Blatiak, D. Papadaskalopoulos & G. Strbac, “Optimising EVs on the Grid with V2G”, Low Carbon Vehicle Conference, Millbrook, UK, 22-23 September 2021

A. Blatiak, D. Papadaskalopoulos, R. Moreira & G. Strbac, “Business Case for Flexibility Services from Electric Vehicle Car Clubs”, UK Energy Storage Conference, Newcastle, UK, 3-9 September 2019

A. Blatiak, D. Papadaskalopoulos & G. Strbac, “Results from the E-Flex Project”, Energy Saving Trust: Fleet Decarbonisation Forum, 7 July 2022

A. Blatiak, D. Papadaskalopoulos & G. Strbac, “Results from the E-Flex Project”, Transport for London: Fleet Decarbonisation Meeting, September 2022

Chapter 2

Background

As energy systems across the globe decarbonise to meet ambitious internationally recognised government targets, the UK is the first government in the world to make a commitment to bring greenhouse gas (GHG) emissions to net-zero by 2050 by law [20]. In the Sixth Carbon Budget set by the Climate Change Committee (CCC), the target for GHG emission reduction was set at 80% by 2035 relative to 1990 levels [21]. The same document outlines the expectation that electricity should have net-zero carbon emissions by 2035, while accounting for large volumes of electric vehicle charging and electrified heating of building.

The whole system benefits of V2G services from EV fleets have been quantified [13], although without considering specific features of markets for energy, Frequency Response (FR) or Distribution System Operator (DSO) services that could enable this. In this chapter, these markets are discussed, in order to review background and context for incentives for EV fleet operators to offer flexibility.

2.1 The Need for Flexibility

The UK Government has committed to bring the UK's emissions to net zero by 2050, outlining its strategy in the Net Zero Strategy: Build Back Greener policy paper [22]. The core source

of generation of the power system in Great Britain is set to become offshore wind, according to the UK Government's Ten Point Plan for 40 GW of offshore wind by 2030 [23], coupled with large scale energy storage (batteries).

To date, there has been a significant reduction in the carbon intensity of generation in GB from 500 gCO₂/kWh a decade ago to 177 gCO₂/kWh [24], [25], due to the increase in renewable energy sources and reduction of the percentage of coal generation used.

Energy system flexibility has been defined as the ability to adjust supply and demand to achieve an energy balance in the energy system [26]. In a power system specifically, it is the ability to respond to changes in demand and supply [27]. In a power system such as that of GB, with more renewable energy connecting to the grid, which is intermittent and not easily predictable, along with more demand from the electrification of the heat and road transport sectors, flexibility is critical. Flexibility enables cost-efficient decarbonisation by adapting to these changes in the supply and demand of electricity. Some research had indicated the value of flexibility in GB could be worth up to £8 billion a year by 2030 [5].

A white paper from the Integrated Development of Low-carbon Energy Systems (IDLES) project entitled "Net-zero GB electricity: cost-optimal generation and storage mix" [28] provides quantitative evidence on how a net-zero (or even net-negative) carbon electricity system could be configured in terms of capacities of various generation types and energy storage. The white paper highlights the key role of flexibility, identifying the need for 142GW of energy storage in a net-zero system where offshore wind fulfils 75% of annual electricity generation with an installed capacity of 108GW. This storage is needed to balance variations in renewable output, avoid grid reinforcement and provide the energy required to meet peak demand. It has been estimated that EV batteries could displace up to 35 GW of battery storage [29].

With smart charging (or V1G) technology, EVs can be providers of flexibility by charging at times of high renewable energy output. With Vehicle-to-Grid (V2G), or bi-directional chargers, EVs are even more capable of providing flexibility to the power system. V2G chargers are becoming more widespread, having recently been demonstrated in the UK through projects such as E-Flex [15] and e4future [30]. There is a growing list of V2G projects available showing

various trials and analysis on V2G Hub [14].

This view for EVs to be providers of flexibility is in line with that of National Grid, the Energy System Operator (ESO) in GB. In the Future Energy Scenarios (FES) report, the ESO sets out a consumer transformation scenario whereby it expects that by 2050, 68% of EV charging demand is shifted away from peak hours and 5 million (out of approximately 30 million) privately owned EVs provide flexibility by the means of V2G-enabled services [31]. Previous research has demonstrated that the impact of accelerated road transport sector electrification on the whole system, as well as local distribution networks, can be achieved most effectively if the flexibility of EVs is sufficiently utilised [29].

2.2 Energy Markets

The UK Government has mandated that all new charge points sold in GB for private (domestic or workplace) use must have smart functionality. This includes communication with and from the charger, reducing charging rate (i.e. charging power levels) when needed, timing charging and being able to provide demand side response (DSR) services [32].

National Grid ESO states in its FES report that for passenger and commercial EVs, consumer engagement in smart charging and V2G technology will be key to minimising increases in peak electricity demand and mitigating the need for expensive network reinforcement [31]. Yet, under current arrangements, EVs are connected at the very end of distribution networks, meaning they participate largely in the retail segment of the electricity market. They are mostly treated like traditional passive domestic or industrial loads. At best, they are treated like smart devices and offered specific tariffs, incentivising them to charge at times of low cost (e.g. Octopus Energy [33]). Despite their smart functionality, a lot of EV owners (through their chargers) do not currently have access to the wholesale market, so do not benefit from choosing when to charge. This limitation is a key challenge that needs to be overcome in order to tap into the flexibility EVs have to offer the power system.

When considering the ability of EVs to discharge with the use of a Vehicle-to-Grid (V2G)

charger, this potential flexibility in the energy market context becomes significant. Currently, the technology exists in order to be able to fully access the energy stored in EVs to charge at times of cheap, renewable energy generation and discharge at times of peak, fossil-fuel based generation (i.e. perform energy arbitrage). The first limitation is the lack of capacity, as V2G chargers are still not an established technology in GB, although this is expected to improve in the coming years. The second limitation is the lack of incentives for EV drivers to perform this arbitrage, which would smooth the demand for energy and mitigate the effects of increased electricity demand from the electrification of the road transport sector. This limitation relates to the previous description of current market arrangement for EVs. Again, Octopus Energy is the only energy supplier at the time of writing that offers an export tariff to EVs [34]. The third limitation is due to the lack of available, established research into the effects of energy arbitrage on battery degradation, often being cited as a concern for EV owners [35].

2.3 Ancillary Service Markets

2.3.1 Transmission System Operator Services

A transmission system operator (or energy system operator in GB, National Grid) must maintain stable and secure grid operation. Inertia, which refers to the physical inertia of rotating masses in thermal plants, prevents blackouts from unexpected generation outages by acting as a store of energy. With the integration of more RES, as described above, and the reduction of fossil fuel generation, lower system inertia means less of this valuable buffer energy being available. The system operator must account for lower inertia by procuring more ancillary services, such as Frequency Response (FR). Such FR services are balancing services which react in the short term to frequency deviations caused by a mismatch in supply and demand [36].

Traditionally, National Grid ESO has procured FR in annual time-frames from generators, demand response and storage devices. This is because generation has largely been flexible and controllable, and demand has followed a variable but predictable shape. Now and in the future,

the GB system will consist of an increasing amount of intermittent RES and a lower level of system inertia. As a result, costs will move from fuel for energy production (as RES has no fuel cost) to operation of this increasingly difficult to balance system. The total cost of providing frequency services (including FR) could reach up to 10% of overall costs [37].

In order to efficiently procure FR services, National Grid has begun to move its procurement horizon closer to real-time in order to give providers a level playing field. This is because some providers of flexibility cannot predict their availability very far into the future (including EVs). National Grid currently procures Firm Frequency Response via monthly tender and has recently completed a weekly auction trial [38]. National Grid is now procuring a new suite of faster-acting frequency services, in order to support operation of an increasingly decarbonised system. The first of these products includes Dynamic Containment (DC), which is procured via a day-ahead auction [39]. It is this FR product, DC, along with the weekly auction trial products, that are used throughout this thesis as balancing service or ancillary service prices. This was the only price data available at the time of conducting the analysis.

There are barriers EVs face to providing balancing services, which are acknowledged throughout the thesis [16]. The technical requirements of providing Dynamic Containment include a 1 second response time, where currently EV charging hardware does not always comply. The minimum bid-size for market participation has been 1 MW in the past, however at the time of writing this is under review, to allow more devices the ability to participate. Nevertheless, there needs to be a sufficient amount of aggregation of EVs in order to participate in these markets. Finally, the level of uncertainty around EV plug-in times and energy usage means that although the day-ahead horizon is more manageable than the yearly, monthly or even weekly one, there are still complexities around forecasting and controlling a high volume of EVs reliably. If the bidding horizon is shorter, this will allow more EVs to participate. Throughout the thesis case studies, the 'upward' or 'high' FR or DC product has been assumed, i.e. responding to a low-frequency event, or a loss of generation on the system, by discharging. However, the mathematical formulations account for both upward and downward events (i.e. where the opposite is required).

2.3.2 Distribution System Operator Services

It is not only for transmission system operation that flexibility is needed, but at a local distribution network level, too. Managing congestion is of great importance to Distribution Network Operators (DNOs) in the UK, as increasing numbers of EVs and heat-pumps are installed. Britain's local flexibility markets are the largest in the world, with an increasing volume of flexibility being tendered and contracted every year. In the 2021/2022 period, 3.63 GW of flexibility were tendered, compared to 2.76 GW in 2021 and 2.1 GW in 2020 [40].

The Energy Networks Association, as part of its Open Networks Project, has set out a group of standard Distribution System Operator (DSO) services, each catering to different network needs. Several DNOs have collaborated to form Flexible Power, which has aligned itself with these guidelines to procure these local services [41], described below.

The first local service is the Secure Service, also known as pre-fault constraint management, is designed to mitigate faults by preemptively reducing network load. It is procured in the week ahead horizon and is expected to be needed on weekday evenings. Payment is made upon committing the availability of the flexible capacity, as well as a utilisation fee on delivery. This is similar to the FR service described in Section 2.3.1, however, utilisation is planned and flexibility providers are notified a week ahead.

The second local service, Dynamic Service, supports the network during fault conditions (i.e. planned outages), which could be during summer maintenance work. It is also procured in the week ahead horizon, includes an availability and utilisation fee, but providers are notified 15 minutes ahead of requirement / utilisation.

The third service procured by Flexible Power is the Restore Service, used for restoring the network in rare, unexpected fault conditions. This is a utilisation-only service, with no payment for declaring availability a week ahead, and providers are expected to respond within 15 minutes of a utilisation call.

EVs need to be aggregated in order to offer availability for these DSO services, which typically

require a minimum capacity of several hundred kilowatts in one zone or group of postcodes. As DSO services are highly postcode dependent, this creates a challenge for aggregators of EVs, whose capacity of flexibility varies geographically. Similar to TSO services, the capacity EVs can offer with smart chargers is limited to the available reduction in charging rate during certain hours, i.e. a reduction from the baseline, which would be evidence for the TSO of the utilisation if this service is called on. With a V2G charger, the capacity offered to DSOs significantly increases, as not only are the EVs available to reduce their charging relative to baseline, but also to inject power to further relieve network congestion during procurement windows.

2.4 Carbon Market

With over half of the FTSE100 companies in the UK committed to eliminating their contribution to climate change by 2050 [42], quantifying the carbon emission reductions achieved by the adoption of EVs is of growing interest. The UK government is also incentivising the transition to EVs by businesses and local authorities [43]. The UK government itself has committed that all central government cars and vans will be zero emission vehicles by 2027. The UK Government has also released a local authority toolkit, encouraging local authorities to identify fleets for electrification, procuring them and the charge-points required [44].

The carbon emissions from EVs must consider the carbon intensity of generation at time of charging the EVs. This data is provided by National Grid ESO [45] on a half hourly basis. However, there are currently no market mechanisms to reflect the value of optimising charging for times of low carbon intensity of generation. This could be of particular value where electricity tariffs are not time-of-use (TOU). One mechanism through which this could be achieved is through the carbon market. At the time the analysis of this thesis was carried out, the price of CO₂ was £50 / tCO₂ equivalent (and hence this is the price used in Chapter 3). The carbon price, set via carbon taxes and Emissions Trading Schemes (ETSs) has been rising, due to ambitious climate policies and global energy commodity prices. However, carbon market devel-

opments worldwide have not been adequate, according to the World Bank [46]. In the UK, the ETS is the established mechanism, with participation limited to energy intensive industries, the power generation sector and aviation.

Some progress has been made by the introduction of a voluntary carbon with carbon credits, which presents a mechanism for high carbon-emitting businesses to offset their emissions by purchasing credits by those who are reducing theirs. The global voluntary carbon market is currently valued at \$300 million [47], compared to the actual carbon market value of \$851 billion [48]. Through the voluntary carbon market, privately owned EVs fleets could offer carbon credits to offset carbon emissions elsewhere. However, this is not yet established and it is unclear whether this mechanism will become widely recognised and adopted by EV fleets.

Chapter 3

Optimal Charging Scheduling of Electric Vehicles with V2G Capability

3.1 Introduction

Storage is one of the available options to help with the adjustment of energy generation or consumption, to ensure that the future low-carbon power system can maintain secure operation. Bidirectional charging, enabled through Vehicle-to-Grid (V2G) technology, can unlock significant storage capacity from stationary EVs that are plugged in. This would result in an improved utilisation of the existing grid assets and in a reduction of the infrastructure investment costs as no redundant equipment would be needed to maintain the system within adequate security levels. Therefore, carbon emissions targets can be achieved, while making significant savings by reducing the need for investment in low-carbon generation, reducing system operating costs and also reducing network reinforcement costs [5]. During the Covid-19 pandemic, a glimpse of this future power system was seen, due to the lower demand and high renewable generation seen in May to July, 2020, in Great Britain (GB). Operating costs in the form of ancillary services increased by £200m compared to the same period in 2019. Research in [49] also indicated that in the 2030 future power system, these ancillary service costs could reach 35% of total operating costs.

In this chapter, a foundational mathematical framework is presented, which optimises the revenues for fleet operators participating in various markets and under different scenarios. Detailed results using real world data are analysed, many of which are included in Appendix B. Conclusions are drawn around the important characteristics of EV fleets that maximise their revenue and make them suitable for V2G operation. In particular, the energy tariff and driving behaviour and their impacts on revenues are highlighted. Carbon emissions are also quantified in the given scenarios, as this is a key metric of how effective a charging schedule is. The way this chapter links to the overall thesis aims is through quantifying the revenues and carbon emissions of EV fleet operation, given current energy and balancing service prices. This can lead to a greater understanding of how EV fleets can operate optimally, providing incentives for the effective decarbonisation of road transport.

3.1.1 Related Work

There has been significant research in the field of modern power systems, investigating how to take advantage of the flexibility EVs have to offer. Often, this is from a power system perspective, where EV charging scheduling, i.e. optimising charging or discharging schedules according to either energy arbitrage or balancing service provision, has been a focus. Early work in this area was developed in [50], which calculated the potential capacity and net revenues for EVs supporting the grid with Vehicle-to-Grid (V2G) technology. The potential for EVs to provide grid services such as peak power, spinning reserves and regulation, was outlined and the societal benefits also discussed. An optimal bidding strategy of EVs participating in electricity markets was formulated in [51], where an aggregator of EVs bids strategically, considering uncertainties in price and driving behaviour. The role of aggregators in the power system is reviewed in [52]. Another operational tool was developed in [11], allowing the aggregator to optimise energy and ancillary services scheduling together. This would allow for higher profits for aggregators, as well as lower costs of EV charging for the customers. EV charging is optimised to minimise carbon emissions and wind curtailment in [53], showing EVs can absorb excess wind generation in GB. More recently, EVs have also been studied as a potential source

of synthetic inertia for low inertia power systems [54] and of reactive power [55]. A technical review on approaches for EV demand management is provided in [12] and covers multiple electric power markets.

A recent review of progress in utilizing EVs for ancillary services is presented in [56] and is done so from several perspectives, including state of the art technology and control methods. An extensive review of charging and discharging strategies, including various objective functions for optimising EVs in the power system, has been carried out in [57]. A common objective function identified in the literature is maximising revenue for the EV owners, fleet operators or aggregators participating in the energy and balancing service markets. In terms of physical constraints and market participation, the basis of modelling EVs as storage is similar to energy storage systems, for example in [58]. It is worth noting that in most power system related studies, the driving behaviour of the EVs is not a focus, rather a predetermined input and often fits a Gaussian distribution based on trends in driving pattern data (examples [51], [59]). This is probably due to the limited real world data available, especially from commercial fleets. In this chapter, real world data leads to detailed insights of fleet operation.

Balancing (or ancillary) services, including frequency response (FR), have also been of particular interest because of their market value [50] and the minimal stress on EV batteries (i.e. when providing availability for the majority of the time, thereby reducing the charge cycling). Utility fleets, with their ease of aggregation by fleet operators or aggregators, can provide the minimum bidding capacity in order to participate in the frequency response market, currently set to 1MW. These fleets are also highly predictable, allowing for a greater certainty that the capacity offered will be met, compared to, for example, aggregating private vehicle fleets [60]. This is another reason the commercial EV fleet data and EV fleet operator perspective were chosen for this chapter and throughout the thesis.

3.1.2 Motivation and Contributions

In this chapter, a Mixed Integer Linear Programming approach is used to maximise revenues for EV fleet operators and quantify the revenues, carbon emissions and other metrics associated

with various EV fleet types and scenarios. It is structured as follows: examined scenarios for commercial EV fleets are outlined in Section 3.2, followed by the mathematical formulations of the models used in Section 3.3. These models include the energy only model, energy and balancing service model, energy and carbon model and multi-service model. In Section 3.4, case studies including results from three selected fleets with three tariff arrangements are presented and discussed. A sensitivity analysis on the carbon price is performed in Section 3.5, and a final conclusion is presented in Section 3.6. Sample raw data used is included in Appendix A, and full results tables of all 12 fleets used in the demonstrator project are included in Appendix B.

In light of the identified suitability of commercial fleets to potentially benefit from V2G technology, Innovate UK has funded the demonstrator project E-Flex [15]. The data and experience from this project, including travel patterns and energy tariff information, are all integrated into this work.

To the best of the author's knowledge, the main contributions of this chapter are:

- Accurate characterisation of flexibility of commercial EV fleets participating in ancillary service markets, using real world data from a V2G demonstration project in the UK
- Comprehensive assessment of revenues of commercial V1G and V2G fleets considering the present GB scenario

3.2 Examined Scenarios

Four models were formulated to reflect and examine the potential modes of operation of an EV fleet. All of these models were used to produce the results discussed in the Case Study Section 3.4 for two modes, smart charging (or V1G) and V2G. The baseline model is dumb charging, where EVs plug in and charge on arrival, was used to demonstrate the added benefit of each of the different examined scenarios. The models are described below:

- **Dumb Charging (Baseline):** this most simplistic mode assumes EVs return to the charger / depot and immediately start to charge up to the required level for the next day.

- **Energy model:** this model optimises for revenue using an import and export energy price. In V1G mode, this means charging when the import energy price is the cheapest. In V2G mode and with a sell price that is significant, EVs will charge when the energy price is lowest and export when the energy price is highest, if it is profitable to do so.
- **Energy and Balancing service model:** this model incorporates both the functionality of the energy model, as well as a balancing service availability. The EVs are paid the availability price when they are plugged in and able to provide the energy if called on. For the V1G case and if the balancing service is upward (meaning generation turn up or demand turn down), the availability is limited and only considers the ability to reduce charging. In V2G mode, fleets are able to offer availability to both discharge and reduce their charging levels if called upon.
- **Energy and Carbon model:** this model incorporates the carbon price, as well as energy price, and maximises revenues for the EV fleet. Carbon is accounted for by considering the price of carbon (i.e. pounds per tonne) multiplied by the carbon intensity of the grid when charging / discharging (the unit of which is grams of CO₂ per kWh). Hence, the cost of carbon is considered and is high when the carbon intensity of generation is high.
- **Multi-service model:** this model considers all elements of the energy and balancing service models, as well as the carbon price. The overall objective is to maximise revenues considering these different services. As with the other models, there are two modes, V1G and V2G.

In summary, the examined scenarios based on the models described are summarised in Table 3.1.

3.3 Mathematical Formulation

Here, the general models outlined in Section 3.2 are formulated as mixed-integer linear programs.

Table 3.1: Summary of Various Models and Examined Scenarios

Model	Charging Mode	Scenario
Baseline	Dumb Charging	1
Energy	Smart Charging	2a
	V2G	2b
Energy and Balancing Services	Smart Charging	3a
	V2G	3b
Energy and Carbon	Smart Charging	4a
	V2G	4b
Multi-Service Model	Smart Charging	5a
	V2G	5b

The charging / discharging power of all EVs can be continuously regulated between 0 and a maximum charging power level and discharging power allowed by the charger, and they need to fulfill a predetermined energy requirement for the scheduled journey within the interval T . The trips that the EVs of the commercial fleet need to take, including the length of the trip in hours and the energy required (i.e. the distance), are known ahead of time. This ensures the user experience is not affected, i.e. the fleet operator will input the trip distance and duration for the EV, according to the work schedule, and the optimal charging schedule will be determined. The energy, balancing service and carbon prices are also known ahead of the one-day time horizon. Although this is in line with the current wholesale energy and balancing service market arrangements, the carbon market is still immature (see Section 2.4) and hence a fixed price is assumed, in line with the current price for carbon.

3.3.1 Energy Model: Scenarios 2a and 2b

The charging schedule for a commercial EV fleet (consisting of EVs denoted by i in fleet I) is optimised over a day-ahead 24-hour horizon of half-hourly time steps t in total time period T . The EV can charge ($C_{t,i}$) and discharge ($D_{t,i}$), acquiring energy needed for travel ($E_{t,i}^{tr}$). In this simplest model, revenues from energy are maximised, according to the objective function (3.1). This considers the buy price for energy per time step (π_t^b) and the sell price for energy per time step (π_t^s).

$$\text{maximise } \sum_{i \in I} \left(\sum_{t \in T} (-C_{t,i} \cdot \pi_t^b + D_{t,i} \cdot \pi_t^s) \cdot 0.5h \right) \quad (3.1)$$

The operating model of the EV includes several constraints. Constraint (3.2) corresponds to the EV battery's energy balance, taking into account the energy needed for travel purposes as well as the losses caused by charging efficiency (η_c) and discharging efficiency (η_d).

$$E_{t,i} = E_{t-1,i} + (C_{t,i} \cdot \eta_c - \frac{D_{t,i}}{\eta_d}) \cdot 0.5h - E_{t,i}^{tr}, \forall t \in T, \forall i \in I \quad (3.2)$$

Each EV is assumed to depart from its grid connection point up to once within the time horizon and subsequently arrive back to its grid connection point only once during the same horizon. This is in line with the trend clearly seen in the real world data, whereby the commercial vehicles follow a schedule of one extended trip from the depot in one day. Outside of this single trip, the EVs are otherwise assumed to be connected to the grid, the hours of which constitute the time period T^{grid} . When the EVs are not connected to the grid, the charging, discharging and balancing services is zero, as per constraint (3.3).

$$C_{t,i} = D_{t,i} = 0, \forall t \notin T^{grid}, \forall i \in I \quad (3.3)$$

Constraint (3.4) expresses the lower (E_{min}) and upper (E_{max}) bounds of the battery's energy content, assumed to be the same for each EV.

$$E_{min} \leq E_{t,i} \leq E_{max}, \forall t \in T, \forall i \in I \quad (3.4)$$

Constraint (3.5) ensures that the energy level of the EV at the start of the day before trips are made ($E_{t_{start}}$) is at the required level (E^{req}) set by the fleet operator, in order to ensure the EV can carry out its work trip.

$$E_{t_{start}i} = E^{req}, \forall i \in I \quad (3.5)$$

Constraint (3.6) states that at the end of a 24 hour horizon, the energy level will return (i.e. be charged up) to the starting energy level. This still allows for different trip lengths and travel patterns on different days.

$$E_{0,i} = E_{48,i}, \forall i \in I \quad (3.6)$$

Constraints (3.7) and (3.8) represent the limits of the battery's charging power ($P^{c,max}$) and discharging power ($P^{d,max}$). The binary variable y ensures that charging and discharging do not happen simultaneously.

$$C_{t,i} \leq y \cdot P^{c,max}, \forall t \in T^{grid}, \forall i \in I \quad (3.7)$$

$$D_{t,i} \leq (1 - y) \cdot P^{d,max}, \forall t \in T^{grid}, \forall i \in I \quad (3.8)$$

3.3.2 Energy and Balancing Service Model

The operating model of the EV includes all energy related constraints described in the Energy Model, constraint (3.2) to (3.8), inclusive.

In addition to the energy optimisation, this model allows EVs to provide an upward balancing service ($BS_{t,i}^{up}$) by reducing charging or increasing discharging in the form of availability. A downward balancing service ($BS_{t,i}^{dw}$) is also considered, where the EVs can increase their charging or decrease their discharging. The objective function (3.9) maximises revenues from balancing services considering charging costs, while meeting the EV trip requirement for energy for travel. Revenues from balancing services are from the availability of upward balancing service multiplied by the upward balancing service price (π_t^{BSup}), as well as the downward balancing service multiplied by the downward balancing service price (π_t^{BSdw}).

$$\text{maximise } \sum_{i \in I} \left(\sum_{t \in T} (BS_{t,i}^{up} \cdot \pi_t^{BSup} + BS_{t,i}^{dw} \cdot \pi_t^{BSdw} - C_{t,i} \cdot \pi_t^b + D_{t,i} \cdot \pi_t^s) \cdot 0.5h \right) \quad (3.9)$$

In addition to constraint (3.3), no balancing services are provided when the EVs are not con-

nected to the grid. This is summarised in constraint (3.10).

$$C_{t,i} = D_{t,i} = BS_{t,i}^{up} = BS_{t,i}^{dw} = 0, \forall t \notin T^{grid}, \forall i \in I \quad (3.10)$$

Constraints (3.11 - (3.12)) ensure that the balancing service availability committed takes into account the maximum power of the charger and whether the EV is charging or discharging.

$$BS_{t,i}^{up} \leq P^{d,max} - D_{t,i} + C_{t,i}, \forall t \in T^{grid}, \forall i \in I \quad (3.11)$$

$$BS_{t,i}^{dw} \leq P^{c,max} + D_{t,i} - C_{t,i}, \forall i \in I \quad (3.12)$$

When committing balancing service availability, it is important to ensure that the energy is available for the service to be sustained for the minimum required time (t_s) if this service was called on. This is captured in constraint (3.13) by considering the state of charge of the battery at the beginning and at the end of the time step. The balancing service provision from EVs only considers availability, rather than utilisation, which is assumed to occur infrequently [13]. Based on this assumption, there is also no penalty applied, should the EVs not meet balancing service utilisation requirements. This is because the constraints in the models used do not consider utilisation, and hence this scenario is not considered.

$$E_{min} \leq \min(E_{t,i}, E_{t-1,i}) - \frac{BS_{t,i}^{up} \cdot t_s}{\eta_d}, \forall t \in T^{grid}, \forall i \in I \quad (3.13)$$

$$E_{max} \geq \max(E_{t,i}, E_{t-1,i}) + BS_{t,i}^{dw} \cdot \eta_c \cdot t_s, \forall t \in T^{grid}, \forall i \in I \quad (3.14)$$

3.3.3 Carbon Model

In this model, revenues are maximised according to objective function (3.15). The carbon intensity of the grid generation ($\tau_t^{CO_2}$) is included as an input, which is multiplied by the price

of carbon ($\pi_t^{CO_2}$).

$$\text{minimize } \sum_{i \in I} \left(\sum_{t \in T} ((C_{t,i} - D_{t,i}) \cdot \tau_t^{CO_2} \cdot \pi_t^{CO_2}) \cdot 0.5h \right) \quad (3.15)$$

This model has the same energy constraints as the model described in 3.3.1, namely constraints (3.2) to (3.8).

3.3.4 Multi-Service Model

The multi-service model includes energy, balancing services and carbon costs, in order to provide multiple services and produce a charging schedule according to maximum revenues.

$$\begin{aligned} \text{maximise } \sum_{i \in I} \left(\sum_{t \in T} \left((BS_{t,i}^{up} \cdot \pi_t^{BSup} + BS_{t,i}^{dw} \cdot \pi_t^{BSdw} \right. \right. \\ \left. \left. - C_{t,i} \cdot \pi_t^b + D_{t,i} \cdot \pi_t^s) + (D_{t,i} - C_{t,i}) \cdot \tau_t^{CO_2} \cdot \pi_t^{CO_2} \right) \right) \cdot 0.5h \end{aligned} \quad (3.16)$$

As this model does not introduce any new decision variables or operational changes, all the constraints that apply to the energy and balancing service model apply, namely constraints (3.2) to (3.14).

3.3.5 Scenario Specific Constraints

Charging Mode

For the smart charging or V1G Scenarios 2a, 3a, 4a and 5a, the EVs are not able to discharge, as the charger discharge power is set to zero. Constraint (3.17) applies.

$$P^{d,max} = 0, \forall t \in T^{grid}, \forall i \in I \quad (3.17)$$

For the full V2G Scenarios 2b, 3b, 4b and 5b, the discharging of the EVs is only limited by the maximum discharging power of the chargers, as expressed in constraint (3.8).

3.4 Case Study Results and Discussion

In this section, case studies based on the models described in Section 3.3 and examined scenarios summarised in 3.1 using real world data are presented. The data sets are described and sensitivity analysis is also performed.

3.4.1 Case Study Input Data and Assumptions

Driving Pattern Data Set

The full original data set has driving patterns for 12 fleets that were in the Innovate UK funded V2G trial, project E-Flex [15]. Travel data for all fleets is summarised in Table 3.2, which characterises the trip start and end times, and Table 3.3, which characterises the trip lengths and energy used for trips. Lastly, Table 3.4 gives the percentage of total time the EVs in the fleet were connected (plugged in) in the nine month trial period. With reference to Table 3.3, it should be noted that trips are recorded as time away from the base depot of the fleet, where the chargers are located. Due to Covid-19, some drivers / employees took the vehicles home and charged them elsewhere. These charging events were not recorded, and instead this stay away from the depot was recorded as an entire trip (which lasted for several days in some cases). The energy used was also counted as one trip, and hence the maximum energy in the data presented is limited to the battery capacity, 40 kWh. It is also worth noting that this data includes weekends and holidays.

It was assumed that all vehicles had a 40 kWh battery for modelling purposes, which was almost always the case. Data is summarised and anonymised for commercial sensitivity and privacy reasons, however, the usefulness for modelling purposes is retained.

Fleet	Trip Start Time (HH:MM:SS)				Trip End Time (HH:MM:SS)			
	μ	σ	Minimum	Maximum	μ	σ	Minimum	Maximum
A	9:13:24	2:19:29	6:05:53	15:07:34	13:32:13	1:38:46	6:56:23	16:11:45
B	10:55:13	2:34:04	6:36:30	16:32:00	12:16:20	2:39:33	6:47:20	18:37:40
C	12:24:02	2:56:36	6:36:10	18:43:08	10:57:57	3:24:30	4:56:00	19:12:30
D	10:27:40	2:16:00	6:06:18	15:57:23	11:49:27	2:49:31	6:16:57	18:59:49
E	11:08:50	2:03:31	7:27:41	15:33:06	14:29:46	1:48:05	8:13:37	17:18:37
F	12:32:52	4:43:20	0:05:17	23:48:04	12:16:24	5:16:35	0:45:04	23:53:52
G	9:30:23	2:14:44	6:00:39	19:57:52	13:04:12	2:16:17	4:59:45	19:46:14
H	11:20:54	2:14:24	7:06:12	17:09:14	12:41:36	2:08:02	7:48:34	17:36:29
I	10:43:10	2:31:30	0:20:32	22:28:38	13:17:15	2:15:24	7:02:04	19:55:28
J	11:38:21	2:44:43	7:09:12	19:33:13	13:15:44	2:42:51	6:52:42	19:44:48
K	12:00:26	2:48:54	6:28:40	18:09:00	11:05:24	2:38:00	7:02:00	17:55:50
L	6:09:30	5:41:15	0:00:34	23:57:39	11:20:19	5:16:13	0:02:57	23:59:59

Table 3.2: All Fleets Trip Start and End Data Summary

Fleet	Trip Length (days HH:MM:SS)				Trip Energy Used (kWh)			
	μ	σ	Minimum	Maximum	μ	σ	Minimum	Maximum
A	7:37:07	22:26:37	0:04:17	12 d 05:14:13	3.62	2.24	0.28	10.24
B	4:53:52	15:27:38	0:04:10	16 d 01:50:50	1.16	1.26	0.10	11.93
C	1 d 17:36:45	4 d 10:30:11	0:04:14	65 d 06:08:30	13.84	25.54	0.09	40.00
D	22:23:41	2 d 14:29:12	0:09:36	18 d 23:43:13	6.46	4.52	0.10	24.54
E	1 d 12:03:24	4 d 00:33:16	0:08:35	24 d 02:19:37	5.74	2.59	0.28	17.47
F	2 d 02:15:07	4 d 12:03:03	0:23:14	22 d 03:42:51	5.35	4.82	0.97	25.26
G	11:12:50	1 d 14:59:02	0:03:21	20 d 01:09:38	5.66	4.38	0.13	38.23
H	3 d 00:38:48	8 d 12:57:23	0:04:17	83 d 05:44:06	5.32	8.21	0.21	40.00
I	18:43:14	3 d 02:24:03	0:08:48	55 d 00:20:20	7.90	12.36	0.25	40.00
J	15:39:39	1 d 15:19:50	0:03:23	17 d 08:37:42	6.40	11.46	0.08	40.00
K	1 d 11:27:19	2 d 12:36:03	0:00:56	33 d 22:01:33	5.21	4.48	0.08	35.26
L	11:16:01	21:42:57	0:13:14	13 d 03:46:00	13.53	9.31	0.33	40.00

Table 3.3: All Fleets Trip Length and Energy Used Data Summary

In Figure 3.1, a summary of the average annual fleet energy consumption per EV and the percentage of total time the fleet EVs were connected to their charge points is shown. Inputs for all fleets except Fleet A (which was collecting data for over 12 months) have been normalised for a year, as the data collection period of the trial was a total of nine months. By showing in colour how the FR revenue varies for Scenario 3b for all fleets, it is clear that connection time affects the FR revenue most. This will be expanded upon in this section.

The raw data, a sample of which is included in Appendix A, was collected as part of the E-Flex project [15] in the form of telemetry data. This data was processed by the project team into trip information by inputting the location of the fleet and grouping drive events together to determine when the EV left the depot and when it came back (i.e. when it was on site and

Fleet	Total Availability (%)
A	89.20
B	64.26
C	33.43
D	75.19
E	68.40
F	87.47
G	82.07
H	38.41
I	75.30
J	62.11
K	33.78
L	77.81

Table 3.4: All Fleets Total Availability Data

connected to the charger). As it was assumed the EVs only charged at the depot (and parked there overnight), this was the only information relevant to this work. If the EVs did not return to depot, their charging elsewhere was not considered and they were deemed to be unplugged. This is a reasonable assumption because fleet operators have no control and do not benefit from their fleets being plugged in or providing services at other locations. From the trip (from depot) information, the author processed the data to create the inputs in the relevant format to this work, i.e. time steps connected to the grid T^{grid} and energy needed for travel E^{tr} for each EV in each fleet. The energy used for each trip was calculated using the distance travelled (included in the GPS data) and manufacturer-specific energy consumption per mile in an urban environment.

Fleets A, B and C have been analysed here, due to these fleets representing different fleet types and current tariffs best. Fleet A has a dual tariff, a high connection time (i.e. the EVs were plugged in at the depot for approximately 90% of the time), along with a low energy consumption for travel. Fleet B has a three-tiered tariff, a connection time close to average among the fleets (approximately 60%), and a close to average energy consumption for travel of 850 kWh. The fleet with the highest energy used for travel (of 1,400 kWh) and lowest connection time of close to 30% was Fleet C, which was also selected for analysis. Fleet C has a flat tariff consisting of one price.

Although Fleets A, B and C have been analysed here in detail, the modelling has been performed

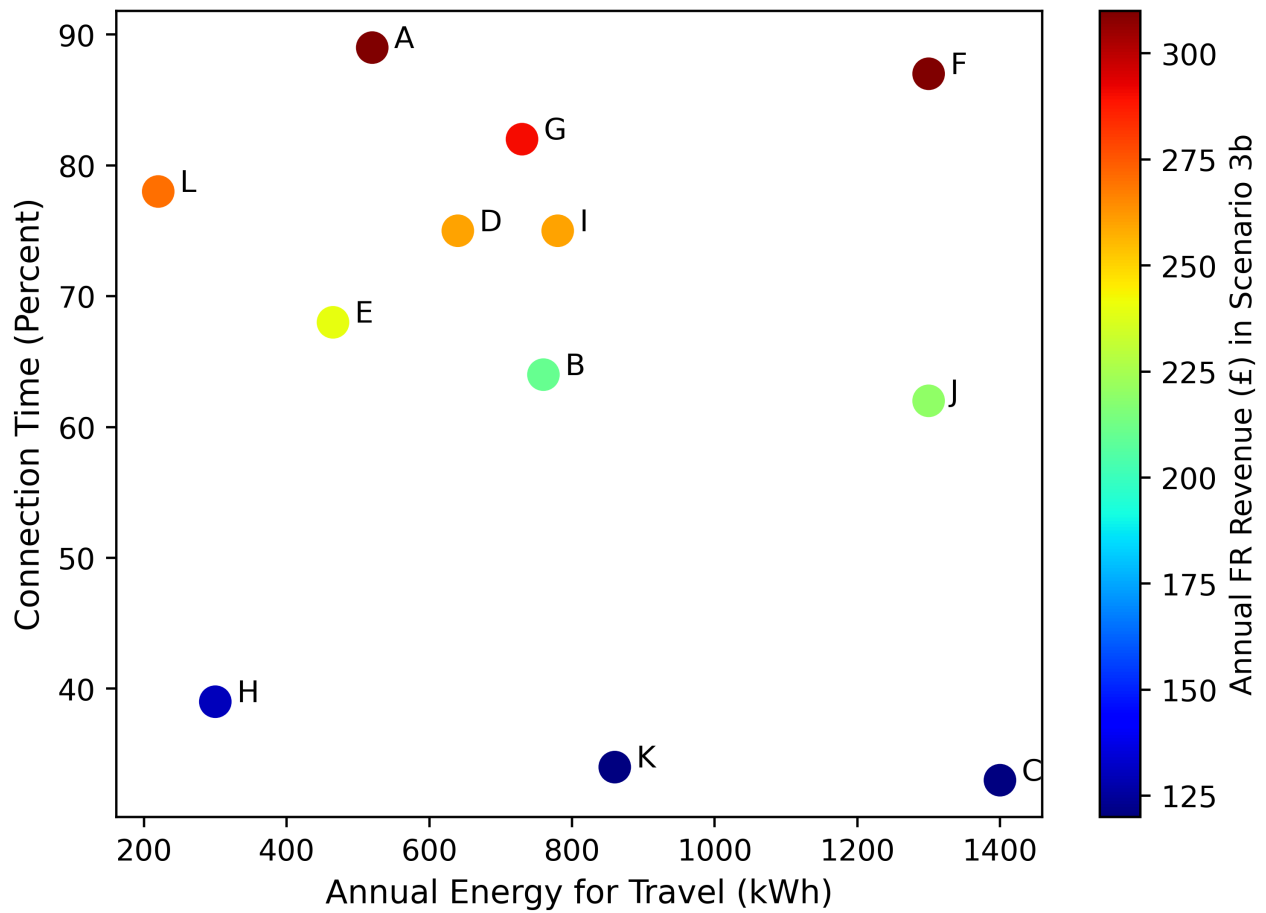


Figure 3.1: Full Data Set of 12 Fleets Comparison

for the full 12 fleets. The full set of individual monthly results of these 12 fleets for the three types of tariff arrangements (described below) are included in Appendix B. Processed fleet driving patterns were used as inputs into the models in order to generate results for the described scenarios. The assumptions used for these case studies are described below:

- t, T : The model was run in 48, half-hourly time steps.
- I, T^{grid}, E^{tr} : 12 fleets in total were used in this analysis, which include real fleet size, grid connection timings and energy used for travel, respectively.
- E_{max}, E_{min} : It was assumed that each EV had a 40kWh battery, which could be charged to maximum capacity, and could be discharged to a minimum of 20%. This allowed fleets and EVs to be compared against each other. It was also a simplification, as some fleets had a mixture of vehicles.
- E^{req} : All EVs were assumed to need a state of charge of 95% by 7am each day. This was approximately in line with most fleet managers on the trial, but was assumed to be the case for each fleet. Again, this was to compare the fleets. This can be expressed as the constraint (3.18) below:

$$E_{14,i} = 0.95 \cdot E_{max}, \forall i \in I \quad (3.18)$$

- η_c, η_d : Charging and discharging efficiencies were both assumed to be 93%.
- π_t^b : Current energy tariffs are real prices from the trial and are either flat (static), dual (day / night), have three different prices throughout the day, or are time-of-use (TOU, which is approximated due to commercial sensitivity). None of the current tariffs have a sell price, just a buy price. This can be expressed as:

$$\pi_t^s = 0, \forall t \in T \quad (3.19)$$

- π_t^{BSup} : Balancing services (frequency response services) are upward only and the prices used are for the Low Frequency Static product, taken from National Grid [61]. This

product is offered in 4-hour Electricity Forward Agreement (EFA) blocks (which equate to 8 half-hourly time steps), as per the current market arrangements for this type of service. It was assumed that the service needed to be maintained for one time-step (0.5 hours). These assumptions and requirements can be expressed constraints (3.20) and (3.21) below:

$$\begin{aligned} \sum_{i \in I} BS_{t,i}^{up} &= \sum_{i \in I} BS_{t+1,i}^{up} = \sum_{i \in I} BS_{t+2,i}^{up} = \sum_{i \in I} BS_{t+3,i}^{up} = \sum_{i \in I} BS_{t+4,i}^{up} \\ &= \sum_{i \in I} BS_{t+5,i}^{up} = \sum_{i \in I} BS_{t+6,i}^{up} = \sum_{i \in I} BS_{t+7,i}^{up}, \quad \forall i \in I, \quad \forall t \in [1, 9, 17, 25, 33, 41] \end{aligned} \quad (3.20)$$

$$BS_{t,i}^{dw} = 0, \forall i \in I, \forall t \in T \quad (3.21)$$

- $\tau_t^{CO_2}$: Carbon intensity of generation was retrieved from the system operator [45].
- $\pi_t^{CO_2}$: The carbon price was assumed to be £50/tonne, which was the approximate market price at the time the analysis was performed [62]. A sensitivity analysis was performed on this value in Section 3.5.

For each set of examined scenarios, three different energy tariff arrangements were modelled:

- Current import tariff**: This was based on the actual tariff of the trial fleet at the time of the trial (which is commercially sensitive data). It is described in a general way, i.e. whether it is flat, dual, three-tiered or TOU. The Octopus Agile TOU import tariff multiplied the wholesale price by a factor, and adds a peak charge between 4pm and 7pm. It also has a maximum charge of 35p/kWh.
- TOU import tariff**: This was based on the Octopus Agile TOU import tariff [63].
- TOU import tariff and TOU export tariff**: The Octopus Agile TOU import tariff was used [63], as well as the Agile Outgoing Octopus TOU export tariff [34]. The Agile

Outgoing Octopus TOU export tariff also a multiple of the wholesale energy price. The exact values are not provided by Octopus (most likely as they are commercially sensitive), so for the purpose of this analysis the export tariff was assumed to be the same as the TOU import tariff.

The Case Studies are summarised in Table 3.5. In the results that follow, separate tables are used to show each tariff arrangement. Note, when discussing the results of each type of tariff arrangement, only the scenario number and letter are used throughout the description in each clearly titled section, e.g. 3a not 3ai, for brevity.

Table 3.5: Summary of Case Studies

Model	Dumb Charging	Smart charging	V2G
Baseline	1i: Tariff	-	-
	1ii: TOU import		
	1iii: TOU import and export		
Energy	-	2ai: Tariff	2bi: Tariff
		2aii: TOU import	2bii: TOU import
		-	2biii: TOU import and export
Energy and Balancing Services	-	3ai: Tariff	3bi: Tariff
		3aii: TOU import	3bii: TOU import
		-	3biii: TOU import and export
Energy and Carbon	-	4ai: Tariff	4bi: Tariff
		4aii: TOU import	4bii: TOU import
		-	4biii: TOU import and export
Multi-Service Model	-	5ai: Tariff	5bi: Tariff
		5aii: TOU import	5bii: TOU import
		-	5biii: TOU import and export

Case Study Metrics

- **Total Cost (£):** This is the total net cost per EV per year. Depending on the particular scenario, it includes energy cost, FR revenue and CO₂ cost. If this total cost value is negative, it means revenue is earned.
- **Energy Cost (£):** Cost of energy to charge (or negative cost of discharging, where

relevant) one EV per year. This includes cost of charging in order to travel and includes energy arbitrage in scenarios where the EV is able to and it is optimal to do so.

- **Carbon Cost (£):** This is the cost of CO₂ in scenarios where CO₂ is considered - it is calculated by multiplying the market price of CO₂ per tonne by the carbon intensity of generation of the charging / discharging schedule. The units are cost per EV per year.
- **FR Revenue (£):** This is the revenue earned by providing the selected frequency response service per EV per year.
- **CO₂ Emissions (kg):** The carbon emissions per EV per year by considering the carbon intensity of generation at the time the EV is charging or discharging.
- **Energy Imported (kWh):** The total energy imported over the period of a year per EV.
- **Energy Exported (kWh):** The total energy exported over the period of a year per EV.
- **Peak Demand (kW):** The maximum demand (in any single time step) that the charging schedule of the relevant scenario produces per EV across the year.

The optimisation problems in this section were all modelled in Python using the Gurobi Python Environment, with a MIP gap of 0.1%. They were run on a machine with a 3.6GHz Intel Core i7-7820X 8-Core processor and 64 GB of RAM.

3.4.2 Fleet A Results and Discussion

Fleet A is the only annual data set in the trial. It comprises of five EVs, which perform maintenance services. It is the same maintenance fleet used for case studies in Chapter 4 and later in Chapter 5. As shown in Figure 3.1, Fleet A is characterised by a high connection time of 90% and a relatively low energy consumption (trips were performed locally).

Fleet A: Current Import Tariff

The annual results per EV in Fleet A are shown in Table 3.6 and in Figure 3.2. Fleet A consists of five EVs but results are shown for the average, so as to better compare across fleets. As this fleet's current import tariff is a dual day / night tariff (with a higher rate applying between 06:00 and 23:59 on weekdays and a lower rate at all other times), Scenario 2a (smart charging or V1G mode) improves the revenues by shifting charging to off-peak hours where energy prices are lower. Adding V2G capability (Scenario 3b) does not add any benefit, due to the energy export tariff being zero. With added frequency responses services (Scenario 3a), EVs are able to further reduce costs in this mode by a small amount. This scenario also reduces peak demand at the site, which has the added benefit of reducing the need for a larger capacity network connection. This is because the charging needs to be low and consistent in order to offer the same reduction of charging across a four-hour EFA block. A similar reduction in peak demand is seen in Scenario 5b, which is also where the only net revenues are generated for V2G. This is where the benefits of having the ability to discharge in response to a frequency event are realised.

Fleet A: TOU Import Tariff

When a TOU import tariff is applied to this fleet, as shown in Table 3.7, it resulted in higher total costs than the current tariff at the site. This is due to higher prices overall. The savings from dumb charging mode (Scenario 1) to smart charging or V1G (Scenario 2a) are lower as a percentage of dumb charging than the current tariff. However, in V2G mode (Scenario 2b), some arbitrage is performed due to some days of negative pricing, where it was profitable to do so. When FR is introduced, a net profit (or negative cost) is seen in the V2G case (Scenario 3b), with the costs in the V1G case being only slightly improved from the energy only case. Considering the carbon price results in higher costs for V1G mode in both Scenarios 4a and 5a, as compared to without. When considering carbon in the V2G case, there is an increase in cost in Scenario 4b as compared to 2b, and a slight reduction in revenues in Scenario 5b compared to Scenario 3b. Energy price and FR price are more significant than carbon, meaning introducing the price of carbon only changed the charging strategies slightly, evidenced by the total energy

Table 3.6: Fleet A Annual Results per EV with Current Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	74.11	74.11	-	-	98.43	520.06	-	4.29
2a: Energy (V1G)	51.49	51.49	-	-	89.06	520.06	-	9.93
2b: Energy (V2G)	51.49	51.49	-	-	88.27	520.06	0.00	9.93
3a: Energy and FR (V1G)	48.70	51.49	-	2.79	89.66	520.06	-	1.24
3b: Energy and FR (V2G)	-258.62	51.49	-	310.10	90.49	520.06	0.00	4.32
4a: Energy and Carbon (V1G)	55.54	51.49	4.05	-	81.08	520.06	-	9.93
4b: Energy and Carbon (V2G)	55.54	51.49	4.05	-	81.08	520.06	0.00	9.93
5a: Multi-Service (V1G)	53.18	51.49	4.48	2.79	89.66	520.06	-	1.24
5b: Multi-Service (V2G)	-254.10	51.49	4.53	310.10	90.49	520.06	0.00	4.32

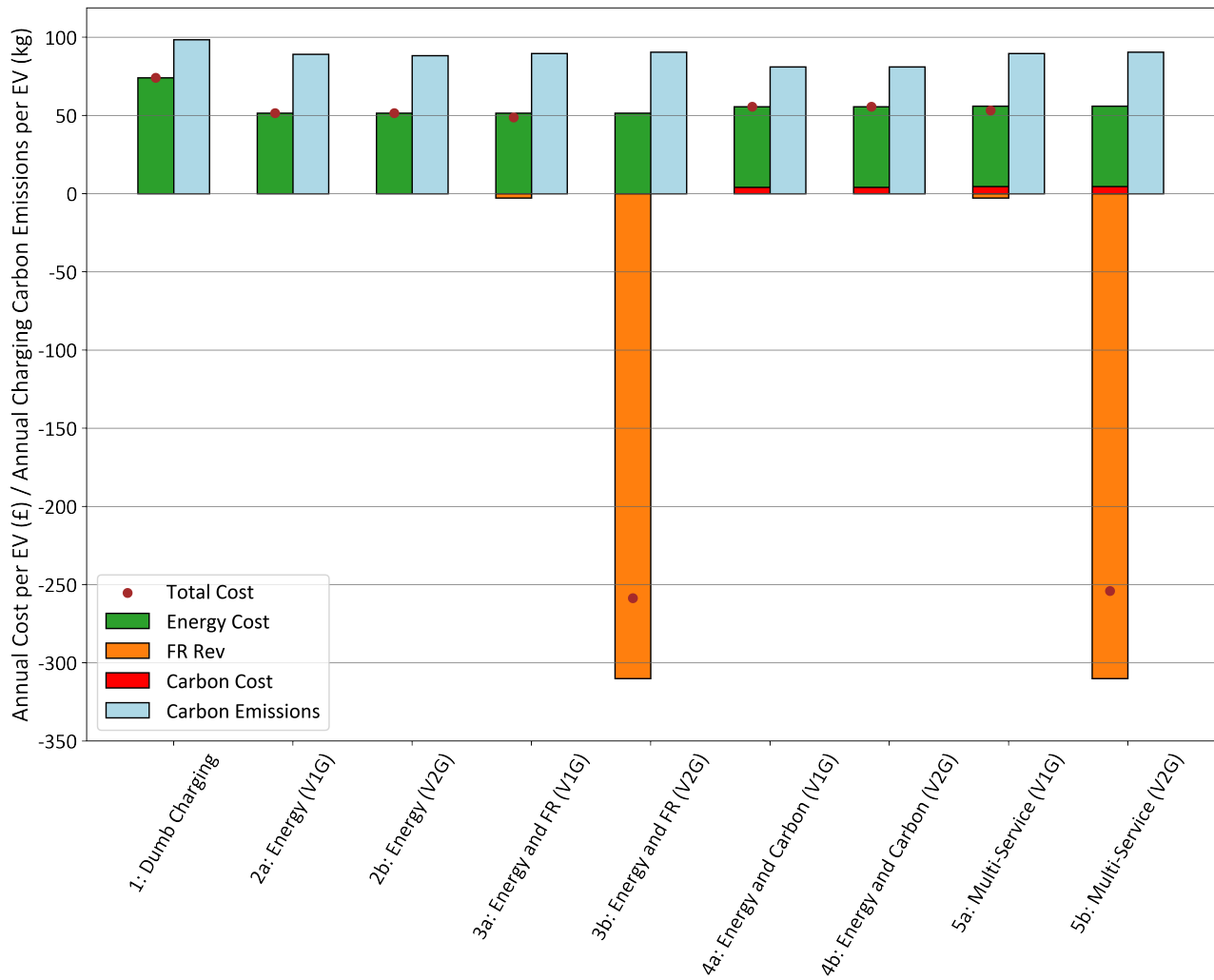


Figure 3.2: Fleet A Annual Results per EV with Current Tariff: Cost and Carbon Emissions

Table 3.7: Fleet A Annual Results per EV with TOU Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	125.63	125.63	-	-	98.43	520.06	-	4.29
2a: Energy (V1G)	102.91	102.91	-	-	85.80	520.06	-	9.93
2b: Energy (V2G)	97.64	97.64	-	-	85.99	666.87	126.98	10.00
3a: Energy and FR (V1G)	102.48	103.02	-	0.54	85.07	520.06	-	9.93
3b: Energy and FR (V2G)	-209.75	98.35	-	308.10	85.82	652.69	114.71	10.00
4a: Energy and Carbon (V1G)	107.02	102.91	4.10	-	82.05	520.06	-	9.93
4b: Energy and Carbon (V2G)	101.38	97.66	3.71	-	74.27	695.33	151.60	10.00
5a: Multi-Service (V1G)	106.64	103.04	4.15	0.55	82.94	520.06	-	9.93
5b: Multi-Service (V2G)	-205.64	98.32	4.06	308.03	81.35	665.53	125.82	10.00

exported in, for example, Scenario 2b compared to 4b. Carbon price is further investigated in Section 3.5.

Fleet A: TOU Import Tariff and TOU Export Tariff

In this final set of results summarised in Table 3.8, a TOU import and export tariff were applied to Fleet A to investigate the costs of each scenario. The most significant effect is seen in the V2G scenarios, where the profitability increases for Scenario 3b, as compared to the current tariff and the TOU import tariff. A significantly higher amount of energy is imported and exported in all V2G scenarios, showing a high amount of arbitrage to maximise revenue in these cases. For an example charging schedule for Scenario 4b, see Figure 3.12. It is in charging schedules that involve a high battery cycling that battery degradation would need to be considered. This is outside of the scope of this thesis but is included in future work in Section 3.6.

Figure 3.3 shows the total annual cost per EV of the three tariff arrangements in V1G mode, broken down into energy cost, carbon cost and FR revenue (which is plotted as a negative cost). Overall, the main difference is between the current day / night tariff and the TOU import tariff, which results in higher costs. These costs are very similar to the TOU import and export tariff case, due to the lack of V2G capability. In Figure 3.4, a clear difference is shown between the different tariff arrangements and scenarios. This demonstrates the advantage of V2G in offering FR services (Scenarios 3b and 5b), as well as energy arbitrage being profitable in the import and export TOU tariff arrangements.

3.4.3 Fleet B Results and Discussion

Fleet B is a maintenance fleet, with most trips being performed during the morning hours and before 3pm. The reason for the lower connection time of 64%, as compared to Fleet A, is that some drivers would not return to the depot but would take their vehicles home.

The total cost and total carbon emission results for Fleet B under the current tariff at the site are shown in Figure 3.5. Note that the full set of monthly tabular results for this fleet (and all others) are available in Appendix B. This Figure was chosen to aid visually displaying key

Table 3.8: Fleet A Annual Results per EV with TOU Import Tariff and TOU Export Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	125.63	125.63	-	-	98.43	520.06	-	4.29
2a: Energy (V1G)	102.91	102.91	-	-	85.80	520.06	-	9.93
2b: Energy (V2G)	-465.01	-465.01	-	-	-1.00	5896.37	4649.98	10.00
3a: Energy and FR (V1G)	102.48	103.02	-	0.54	85.07	520.06	-	9.93
3b: Energy and FR (V2G)	-728.15	-453.68	-	274.47	11.05	4993.97	3869.49	10.00
4a: Energy and Carbon (V1G)	107.02	102.91	4.10	-	82.05	520.06	-	9.93
4b: Energy and Carbon (V2G)	-466.37	-464.71	-1.66	-	-33.23	5892.70	4646.80	10.00
5a: Multi-Service (V1G)	106.64	103.04	4.15	0.55	82.94	520.06	-	9.93
5b: Multi-Service (V2G)	-728.02	-454.03	-0.12	273.86	-2.46	4949.98	3831.44	10.00

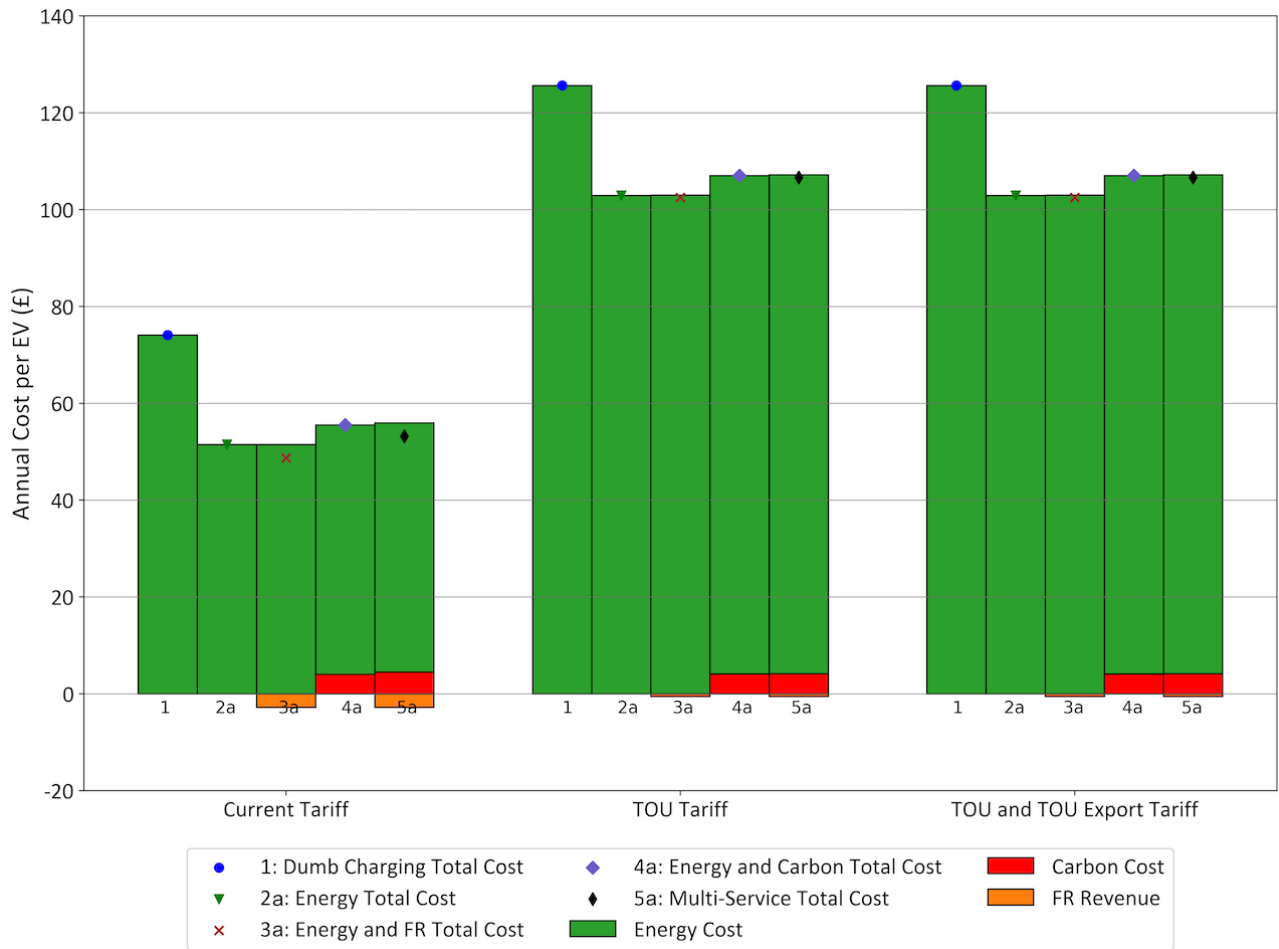


Figure 3.3: Fleet A: Tariff Arrangement Comparison with V1G Scenarios

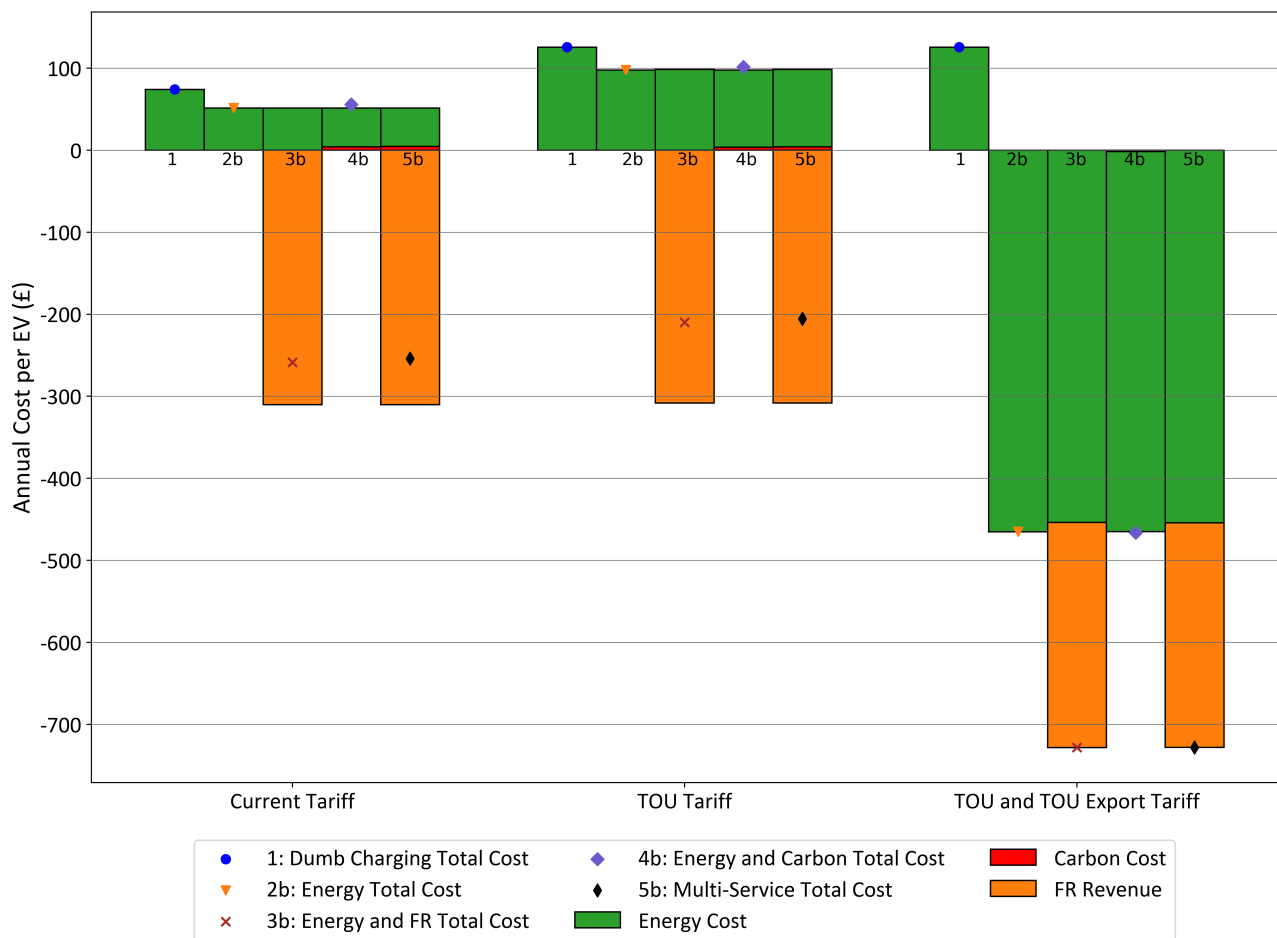


Figure 3.4: Fleet A: Tariff Arrangement Comparison with V2G Scenarios

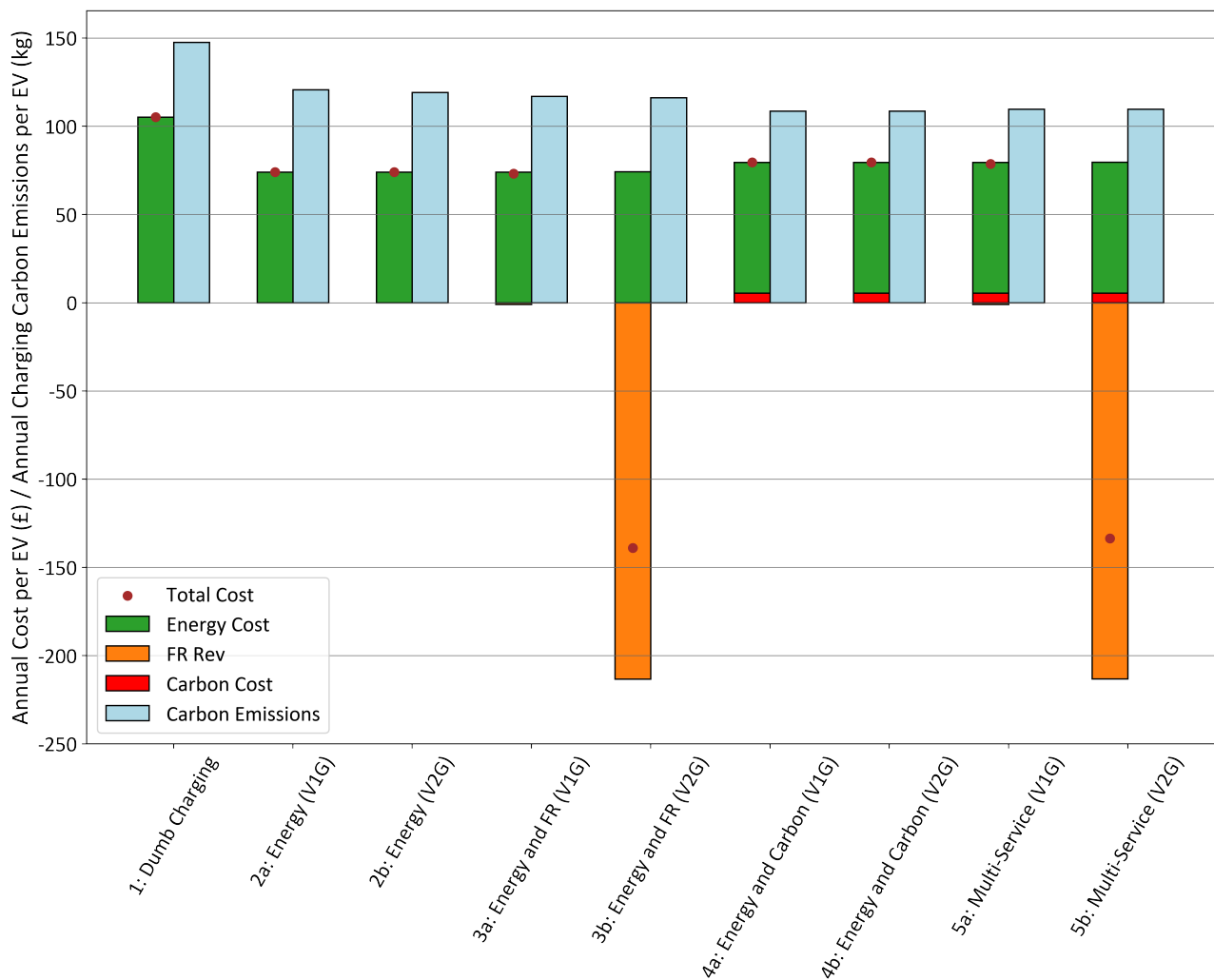


Figure 3.5: Fleet B Annual Results per EV with Current Tariff: Cost and Carbon Emissions Results

results. This site has a three-tiered tariff, with the highest price for weekdays during the day (06:00 to 18:59), one price for weekday evenings (19:00 to 23:59) and weekends, and the lowest price applying on weekday nights (00:00 - 05:59). Here, this is a clear reduction between the dumb charging scenario and the V1G scenario 2a, due to the three-tiered tariff and shifting charging to off-peak times. The difference when applying V2G in Scenario 2b or FR to the V1G case in Scenario 3a is not very different from this total cost and total carbon emission value. When energy and FR are modelled in Scenario 3b, as with Fleet A, this results in the most profitable scenario. This is because V2G allows for high FR service participation when EVs are connected. The net cost is negative, resulting in profits. When examining Scenarios 3b, 4a and 4b, the results are similar to that of 2a, 2b and 3a, only with an added carbon cost, further increasing the cost of these scenarios. The multi-service Scenario 5b shows a similar result to that of 3b, only with a slightly lower net revenue, given the cost of carbon.

Annual Fleet B results per EV for all three tariff arrangements in V1G mode are shown in Figure 3.6. This provides an overview of the benefits of each tariff arrangement in the V1G case. The difference between the current tariff and the TOU import tariff is the largest, with the current tariff being favourable in terms of cost saving. Here, there is no real difference between the TOU import tariff arrangement and the TOU import and TOU export tariff arrangement, due to the lack of ability to discharge in V1G mode.

The same comparison is made for different tariff arrangements in V2G mode in Figure 3.7. Here, the most significant difference is upon introducing a TOU export tariff. In these cases, any V2G strategy results in profit (or negative cost). The highest profit is made in Scenario 3b, where carbon price is not considered.

These results show the potential of V2G in combination with a TOU export tariff and FR provision in unlocking new revenue streams for EVs.

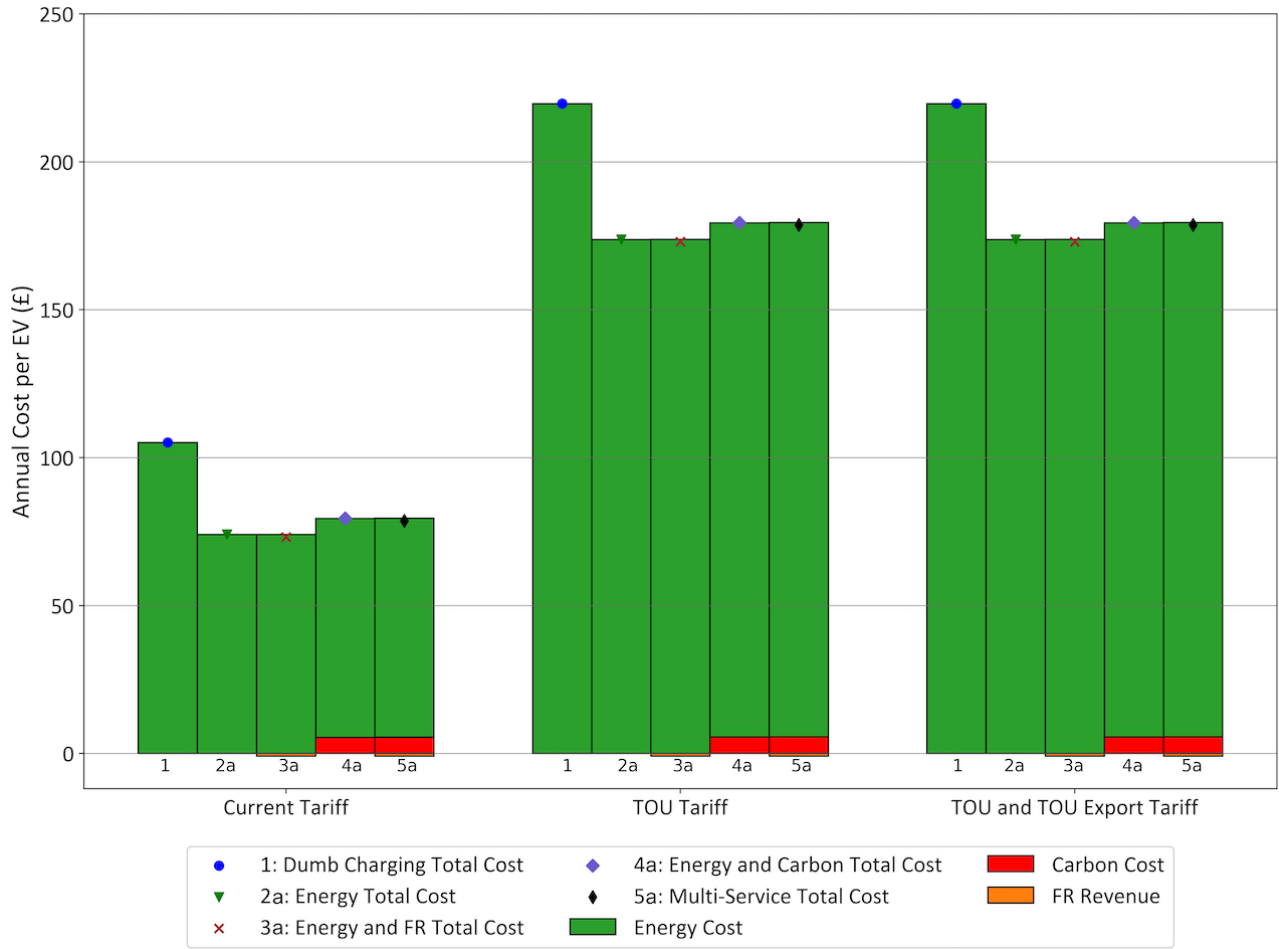


Figure 3.6: Fleet B: Tariff Arrangement Comparison with V1G Scenarios

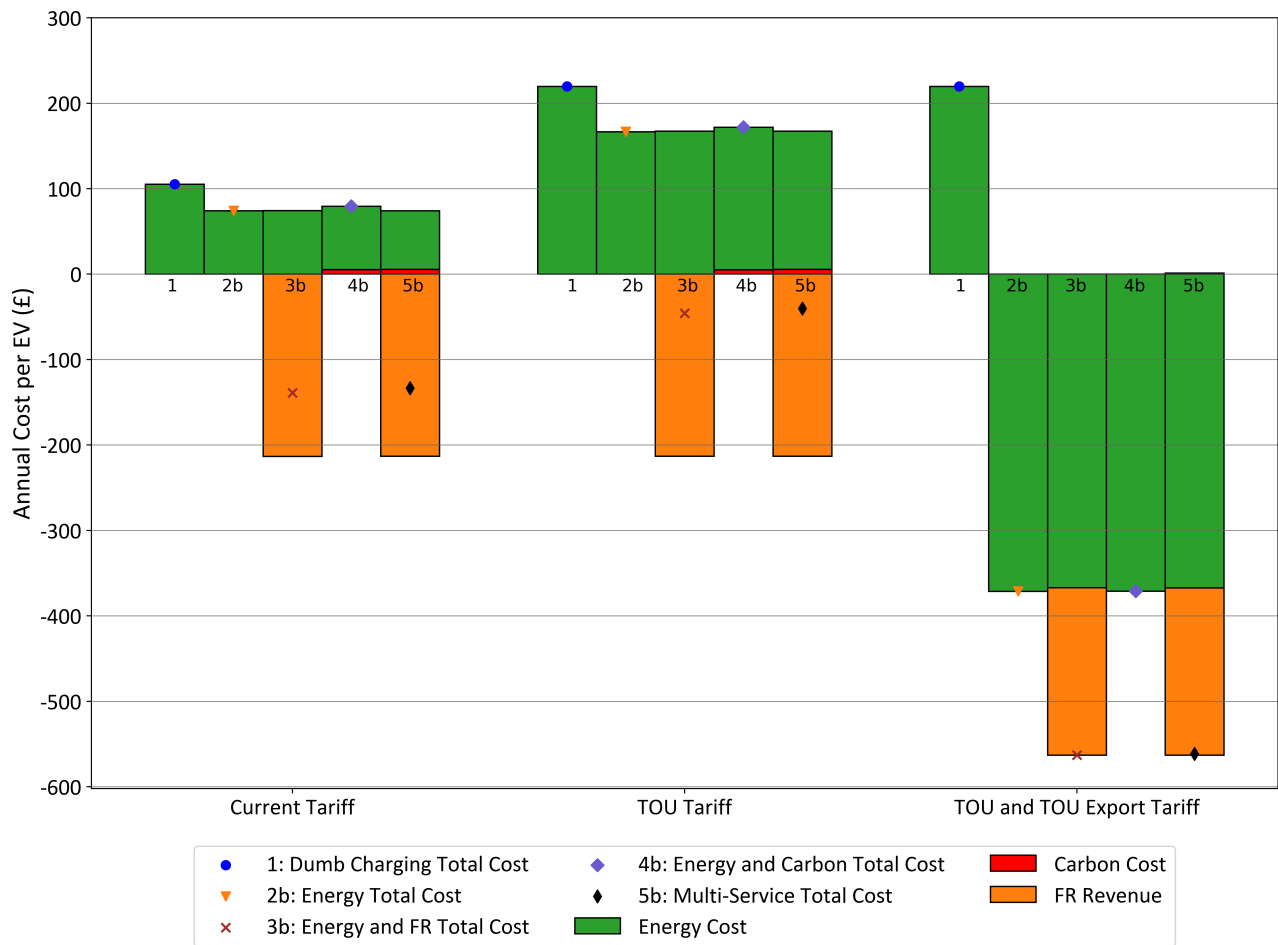


Figure 3.7: Fleet B: Tariff Arrangement Comparison with V2G Scenarios

3.4.4 Fleet C Results and Discussion

Fleet C is a delivery fleet and is characterised by high energy consumption as well as low connection time of 33% due to long journeys made. Similar to Fleet B, some EVs did not return to depot over some periods. Fleet C has a flat tariff, meaning the price does not vary at all.

As expected from a fleet with a flat tariff, the costs under current tariff arrangement in Figure 3.8 show no difference in cost of energy across all scenarios. The carbon emissions do vary, due to the different times the EVs charge. For instance, the carbon emissions in the dumb charging scenario (Scenario 1) are higher than in Scenario 2a, because the charging moves from being immediately on arrival. It makes no difference to the cost outcome, for which the model is optimised, but the resultant carbon emissions are lower when charging later, given the EVs return close to peak carbon emissions. When introducing a carbon price in scenarios 4a, 4b, 5a and 5b, carbon emissions are lowered by considering the carbon intensity of generation. Due to the flat tariff presented here, the effect of a carbon price on carbon emissions is more evident than it is other fleets. For Fleets A and B, there is not as much difference in carbon emissions between scenarios, due to the fact that energy price has the highest impact on overall cost.

Similar to Fleets A and B, results in Figure 3.9 show that in V1G mode, the biggest difference is when introducing a TOU import tariff. The costs in each scenario increase.

Whereas in Fleets A and B each V2G scenario with a TOU export tariff was profitable, with Fleet C this is not the case, as shown in Figure 3.10. The costs of scenarios 2b, 4b and 5b decrease significantly with the introduction of a TOU export tariff, due to the ability of the EVs to perform energy arbitrage and provide FR services. However, only Scenario 3b results in profit. This scenario is consistently the most beneficial across all fleets.

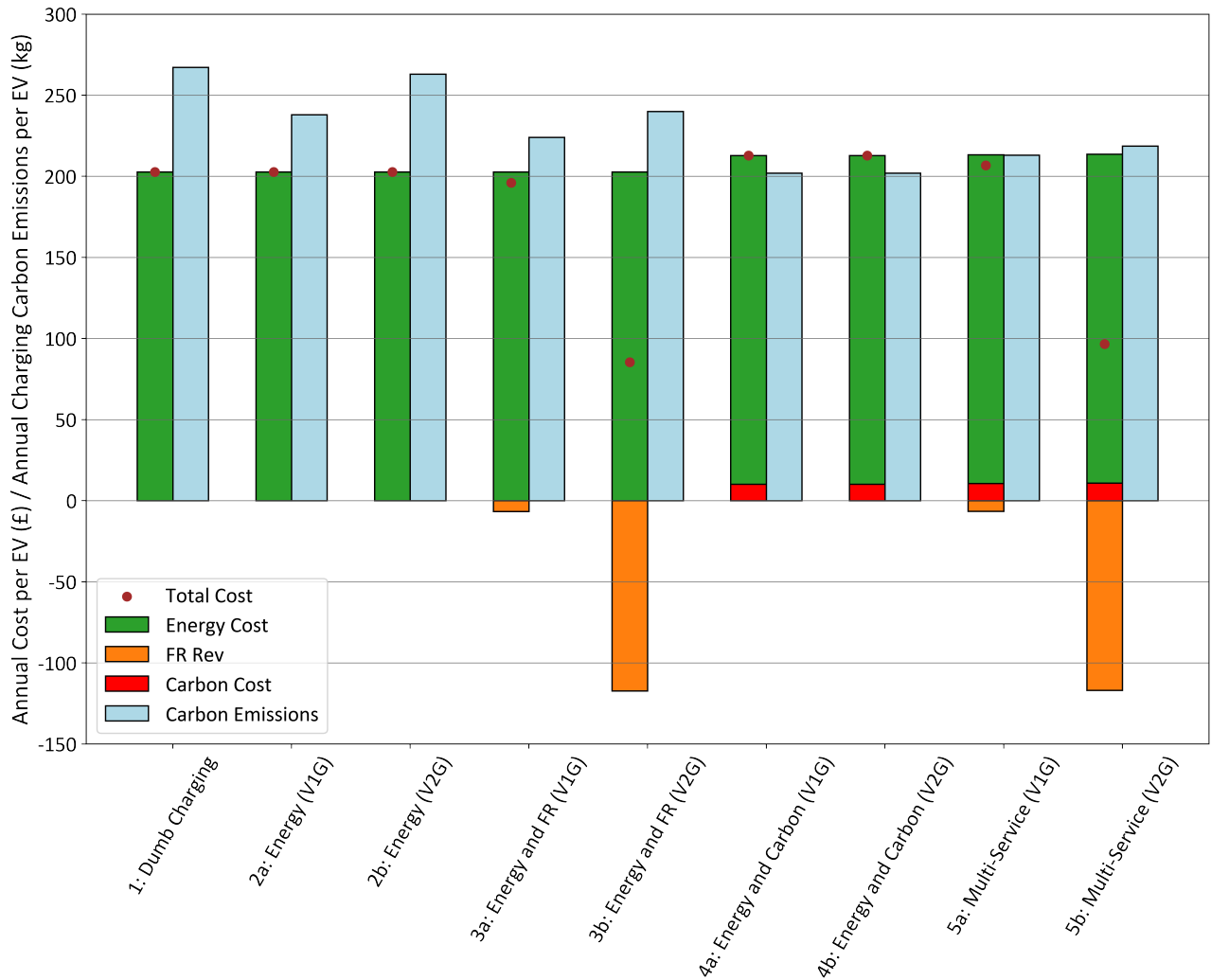


Figure 3.8: Fleet C: Annual Results per EV with Current Tariff: Cost and Carbon Emissions Results

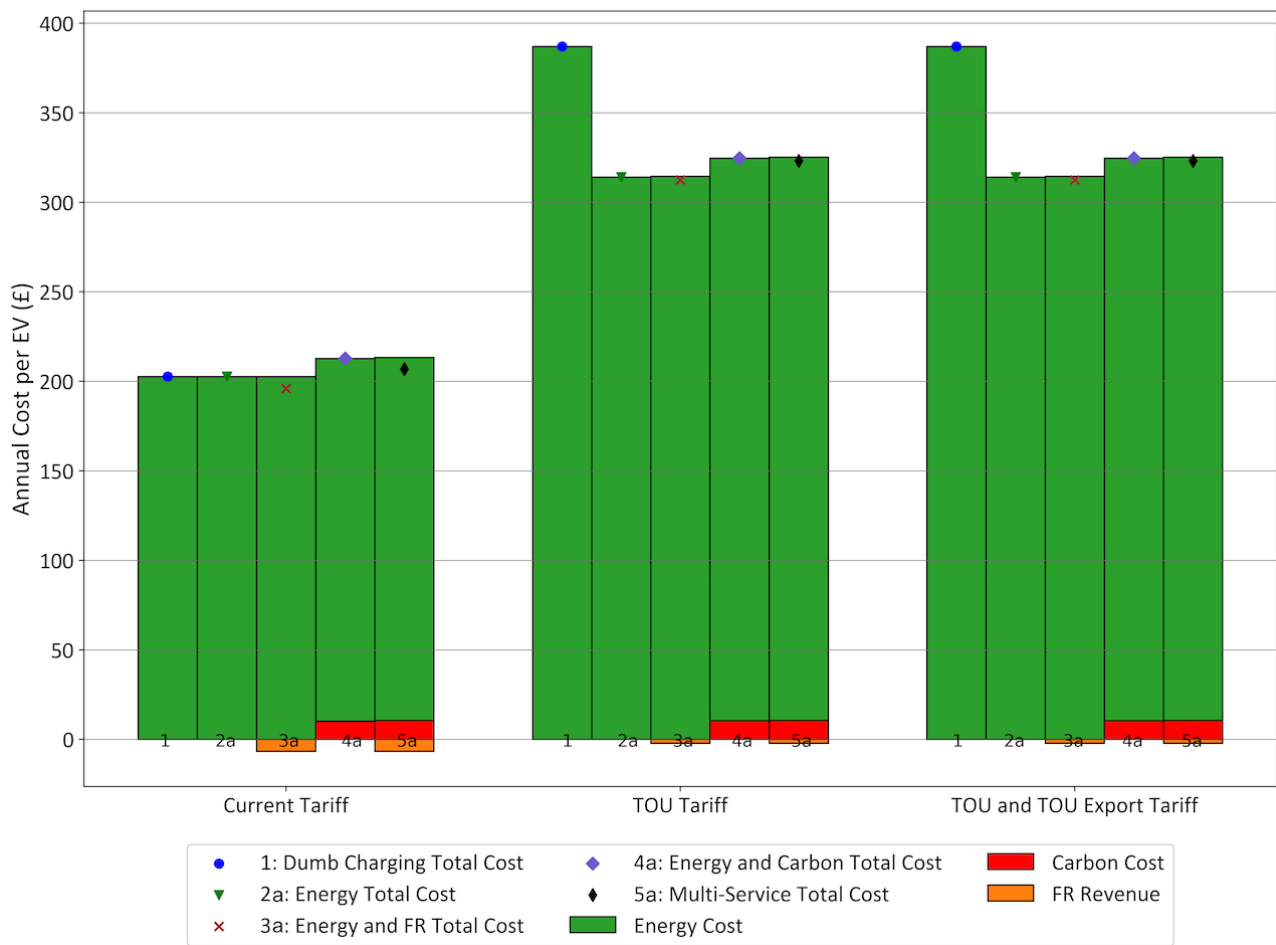


Figure 3.9: Fleet C: Tariff Arrangement Comparison with V1G Scenarios

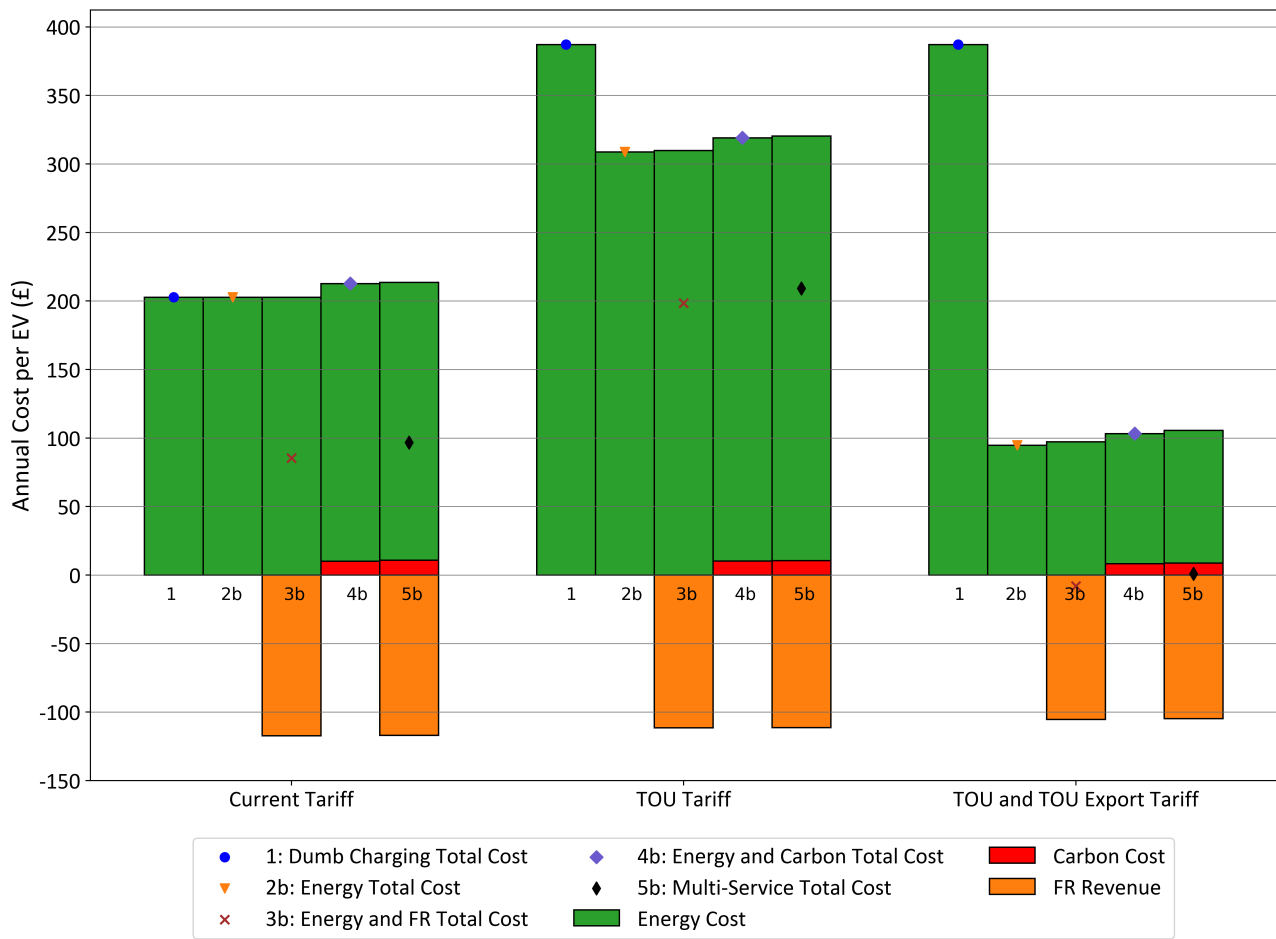


Figure 3.10: Fleet C: Tariff Arrangement Comparison with V2G Scenarios

3.5 Sensitivity Analysis

Scenarios with a carbon price, i.e. Scenarios 4a, 4b, 5a and 5b, with a TOU import and TOU export tariff were modelled with different carbon prices in order to investigate the effect of this on costs and charging schedules. Throughout Section 3.4 above, a carbon price of £50/tonne was used, the current market price at time of writing [62]. Figure 3.11 shows Fleet A results for carbon prices of £50/tonne, £250/tonne and £500/tonne. The total cost for V1G scenarios (i.e. Scenario 4a and 5a) increases with carbon price and the total revenue (negative cost) of V2G scenarios (i.e. Scenario 4b and 5b) increases also.

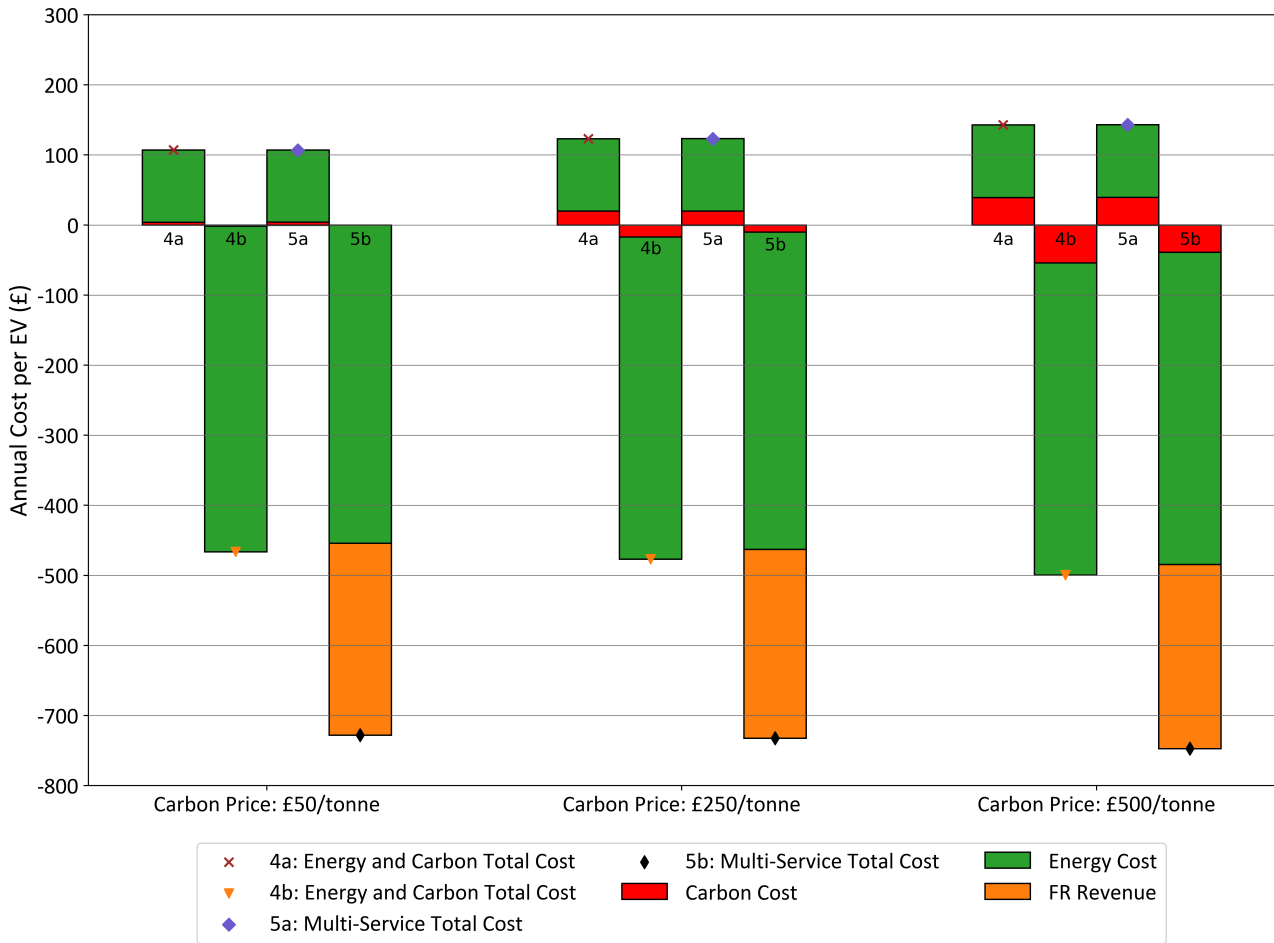


Figure 3.11: Effect of Increased Carbon Price on Annual Cost per EV for Fleet A

To illustrate the change in charging strategies that resulted, Figure 3.12 shows a charging schedule of a day for Scenario 4b of fleet A with a negative cost of -£1.51. This is broken down into -£1.54 in energy costs and £0.03 in carbon costs. Here, no FR is offered but energy price

and carbon price are considered. The TOU import tariff (labelled as Energy Buy Price) has an evening peak, during which the EVs discharge. The EVs perform energy arbitrage by charging back up at night, when the price is lower. The carbon price roughly follows the energy price (except for the peak hours), demonstrating the correlation between energy price and carbon intensity of generation. This occurs because the marginal or running costs of renewable energy is very low, as there are no fuel costs. Therefore, at times of renewable energy generation, energy costs are low and the carbon intensity of generation is also low.

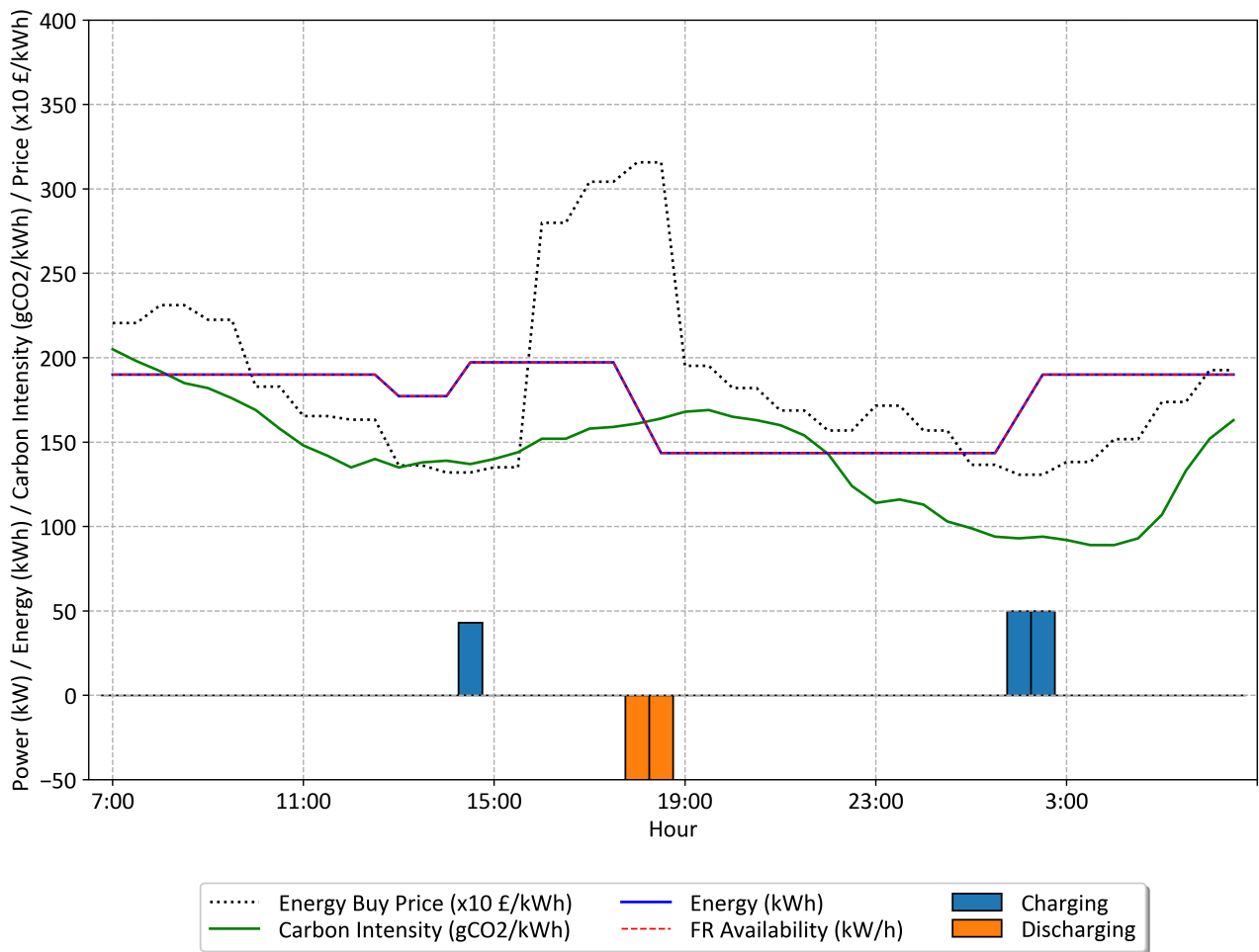


Figure 3.12: Example Charging Schedule for Scenario 4b, Fleet A, CO₂ Price of £50/tonne

With the carbon price increased to £500/tonne, the charging schedule for the same day is shown in Figure 3.13 for comparison. The cost for this day had increased significantly to £0.05, no longer earning revenue. This is broken down into -£2.32 in energy costs and £2.37 in carbon costs. It should be noted that this example shows a large increase in cost, overall the annual results show only a marginal one. With this higher carbon price, the EVs discharge completely

during peak hours, where both the export energy price and carbon prices are high. The EVs charge up again, fully, when the energy and carbon prices are low. Here, although the EVs earn more from the energy arbitrage they perform, this is almost balanced out by the carbon costs resulting from this strategy. More energy in total is charged and discharged (or arbitrated) to compensate for the higher cost of carbon.

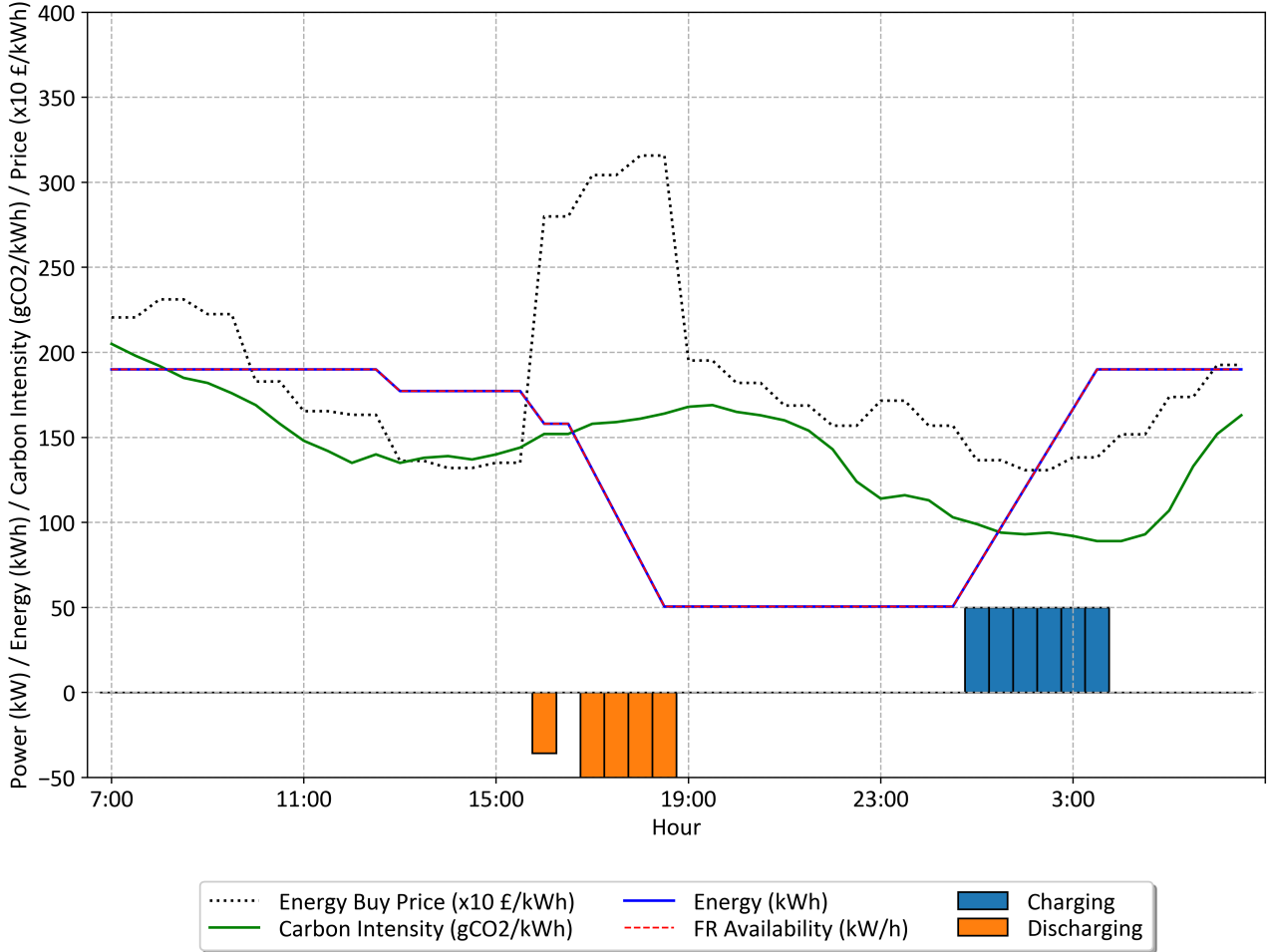


Figure 3.13: Example Charging Schedule for Scenario 4b, Fleet A, CO₂ Price of £500/tonne

An example of the effect of a higher carbon price on Scenario 5b is shown in the comparison between Figure 3.14 and 3.15. Where the price of carbon is £50/tonne and the price of energy is relatively flat (this is because the TOU import tariff price is capped at £33p/kWh), FR availability is offered, as shown by the red shaded area. This day is a weekend day, where no trips are performed and all EVs are connected. Due to the high TOU import price (labelled in the Figure as Energy Buy Price), no arbitrage is performed. The cost for this day is -£3.90, i.e. it is a revenue earning charging schedule. This is made up purely of FR revenues, as no

energy is charged or discharged.

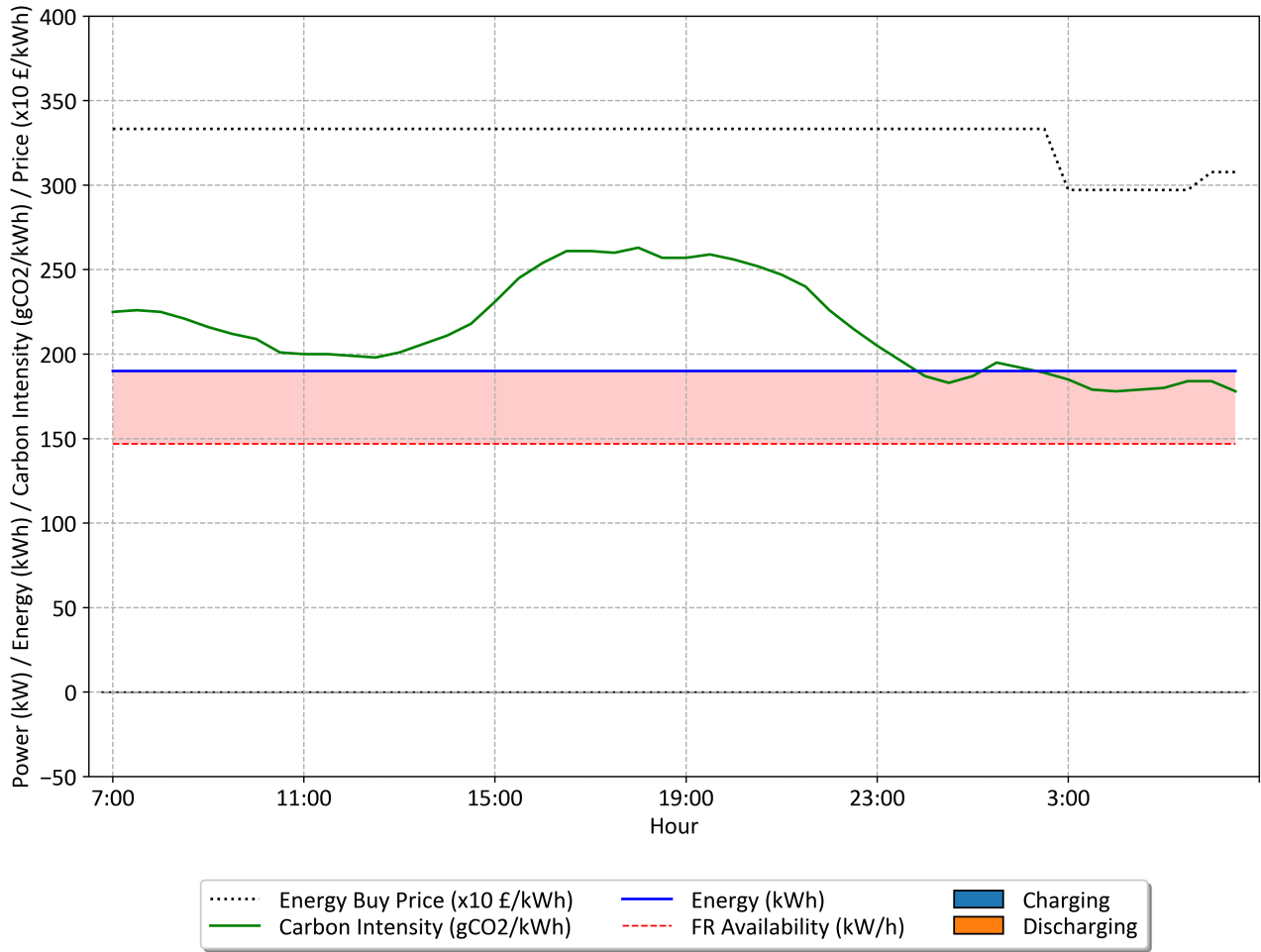


Figure 3.14: Example Charging Schedule for Scenario 5b, Fleet A, CO₂ Price of £50/tonne

Figure 3.15 shows the effect of a higher carbon price of £500/tonne on the same day's schedule. The costs decreased further to a total of -£4.71, to become more revenue generating. This consists of an energy cost of -£0.09, a carbon cost of -£1.02 and a FR revenue of £3.61. Although the FR revenue decreased, by discharging the EVs when the carbon price was high and discharging them when the carbon price was lower, the net benefit was higher. This was a clear example of a change in strategy, where the increase in carbon price meant services are 'competing'.

In conclusion, the increase in carbon price results in an amplification of either positive or negative costs, depending on the scenario. It was shown that when the carbon price is £500/tonne, the charging schedules of the EV fleet change. For V2G schedules where only energy and carbon are considered (Scenario 4b), a similar pattern may be seen. For V2G multi-service schedules

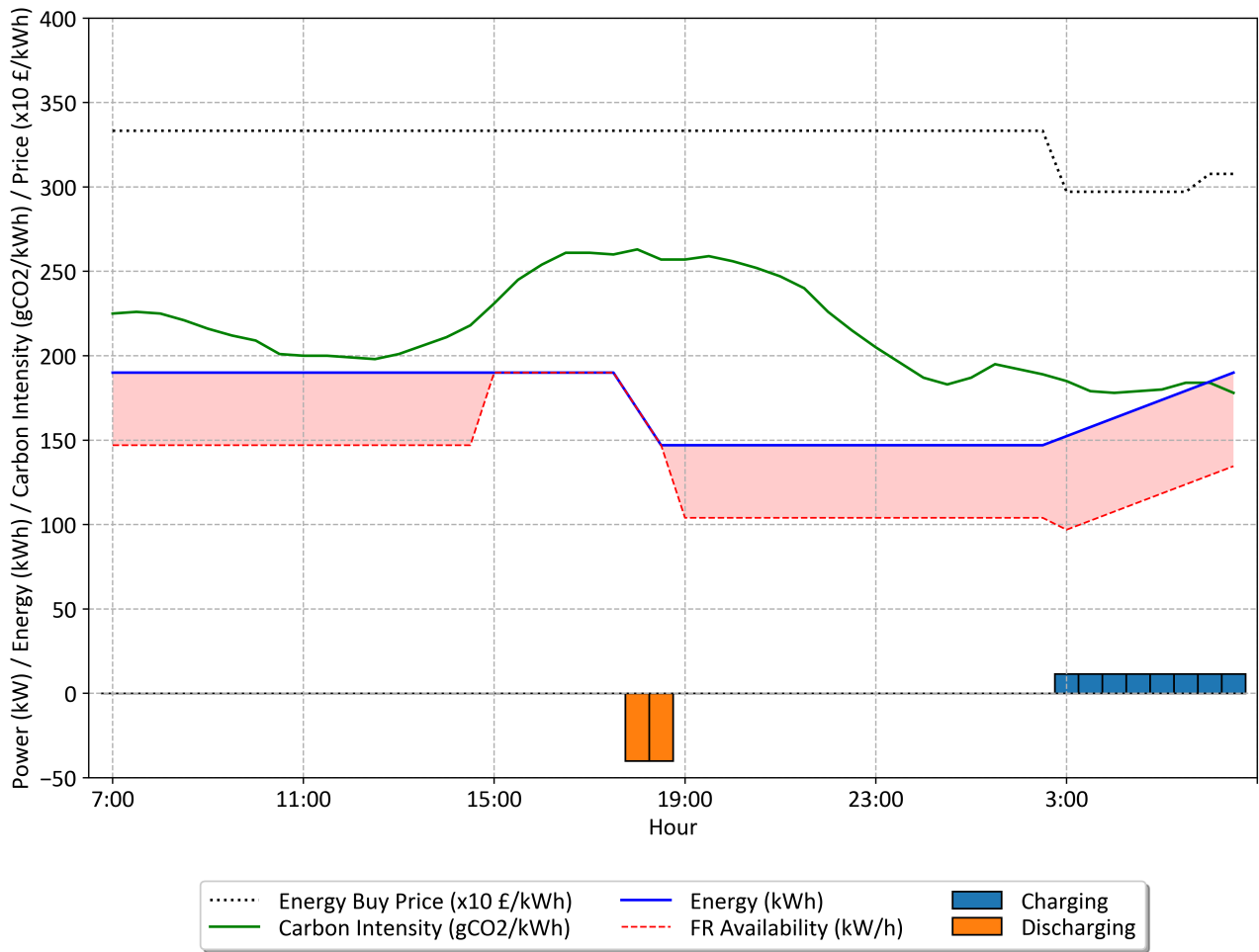


Figure 3.15: Example Charging Schedule for Scenario 5b, Fleet A, CO₂ Price of £500/tonne

(Scenario 5b), a new strategy was implemented, showing the higher price resulted in carbon being a competing service. In both examples, more energy was exchanged, leading to greater battery cycling. These results imply the impact of higher carbon price increases in the future will depend on the modes (i.e. availability of V2G infrastructure), markets (e.g. FR) and tariffs (including export tariffs) they can access.

3.6 Conclusion

In the context of investigating the role of EVs in the power system, this chapter has laid out a foundational mathematical framework and quantified revenues from EV fleets from the perspective of EV fleet operators. Various examined scenarios explored the revenues available, in light of a variety of real EV fleet travel patterns.

Results showed that energy tariffs have a very significant impact on EV charging costs, and that a time-of-use tariff is not always preferable. This is likely due to high wholesale energy market prices, which directly affected the TOU import tariff used in the analysis. Dual or three-tiered energy tariff are usually fixed over several years, and so were not affected by shocks to the energy markets that were reflected in the high wholesale energy market price. By optimising for price, these dual or three-tiered energy tariffs can be enough to reduce costs of charging, especially in the V1G case. An export tariff in combination with V2G unlocks significant revenue from energy arbitrage, as well as FR provision. At its present price of £50/tonne, the carbon price does not significantly impact charging strategy or costs. This means the carbon intensity of generation does not influence when the charging occurs. However, it was observed that there was a correlation between energy price and carbon intensity of generation; when energy prices are low, carbon intensity of generation is generally also low.

The higher the proportion of time the EVs are connected, the higher the FR revenue generated. This is because the availability of the EVs is the most important aspect of providing FR services. Although detail was provided for fleets A, B and C, this conclusion is supported for all 12 fleets in Figure 3.1.

The insights gained from the case studies included which charging modes and business models were most beneficial in terms of revenues and carbon reduction. Across all scenarios and fleets, the V2G mode with energy with FR services had a consistently negative cost, earning the fleets the most revenue. Of course, certain assumptions were made here as to the accessibility these fleets have to the FR market, but the potential of EVs to provide these services given their connection times is high.

The next chapter will address two major themes that were not covered in this chapter but that are part of the core question of this thesis: travel scheduling and the future power system. The next chapter will seek to answer the question, what will the value of simultaneously scheduling both EV charging and trips be in the future power system? It will also address the question, how are the optimal charging schedules created in this chapter likely to change in the future power system?

Chapter 4

Optimal Trip Scheduling of Electric Vehicles with V2G Capability

4.1 Introduction

Much of the literature on EV load coordination with V2G technology focuses on charging strategies. The trips the EVs make are inputs to these approaches, and not an additional element that the fleet operator has control over. At a commercial site, the charging is organised by the facilities manager and the fleet trips are organised by a fleet operator - so often disconnected. In other sectors, too, there is the transport planning industry and well-known vehicle routing problem and solutions, and there are the electric infrastructure and energy companies. It has been observed that these two elements, broadly transport and energy, are not coordinated [64]. So, there is an opportunity to better integrate the transport and power systems, with the extra storage capacity offered by the EV fleet to the system operator. This could lead to better use of surplus renewable energy generation, for instance.

Building on the foundational models presented in Chapter 3, this chapter proposes a new approach. To take charging coordination a step further, this chapter quantifies the maximum potential revenues to be gained by a commercial EV fleet operator from simultaneously scheduling its trips on a day-ahead basis, as well as its charging. This allows the fleet to complete

its trips (with user defined trip length and distance), while taking advantage of fluctuating energy and ancillary service prices. A mathematical framework for optimal trip scheduling is proposed, formulated as a mixed-integer linear program, which is then applied to several relevant scenarios of the present and future electricity system in GB. This chapter also links to the overall aims of this thesis by proposing a solution to the problem of the future power system integrating EVs, increasing the incentives and coordination of EV charging to create a win-win scenario for the transport and energy sectors.

4.1.1 Related Work

Electric vehicles research exists in many fields and from many perspectives. Regarding their interaction with the electricity network, there are two established fields that investigate this issue, power systems and transport studies. The latest developments in these fields will be summarised in this section, describing the state of the art. There is one emerging field where these disciplines are beginning to overlap, and where the content of this chapter makes a contribution. It is important that both perspectives, power systems and transport studies (which can be generally summarised as the charging scheduling of the EVs and the travel scheduling of the EVs), are both considered as transport is electrified. This is due to the increasingly relevant and complex interaction between energy and transport systems moving forward.

A limitation of power system studies of EV charging and discharging schedules (the related works of which are outlined in Chapter 3) is that most do not consider vehicle trip timings or routes as decision variables in their approaches (i.e. driving patterns are either fixed inputs or the uncertainty in plug-in times is accounted for and modelled). There is another field that focuses on these issues but without the power system dimension. The Vehicle Routing Problem (VRP), specific to EVs (E-VRP), approaches the optimal operation of EVs from the driving pattern and infrastructure perspective. Here, the objective function is often to plan the optimal route, as opposed to the optimal charging schedule, as often seen in power systems research. This optimal route takes into account traffic, charging needs and other constraints [65]. A

limitation of these works is that although the prices of the use of charge-points are considered, these are not clearly linked to ancillary service market price. The prices are described as being related to electricity ‘cost’, service and parking fees [66]. Recent work [67] has integrated the optimal charging schedule with a vehicle routing problem, to produce maximum revenues for various agents, while also solving which route EVs should take. In [68], a mixed integer linear program was formulated to create charging schedules for EVs, as well as an optimal route, which considered distribution network constraints. The approach taken in [69] also involved charging schedule optimisation and routing the EVs under time delay tolerance. Time delay tolerance is related to how long an EV is willing to wait in a queue to charge. A limitation of these works is that they do not consider the perspective of commercial fleet operation, nor do they account for ancillary service participation or prices. In other words, the element of tapping into the flexibility EVs have to offer the power system is not fully explored in combination with the optimisation of the trip itself. In order to effectively integrate EVs, making them useful to the system operator, as well as maximise their own revenues, it is important that the ancillary service market is also considered.

The provision of ancillary services, which is significantly higher with bi-directional charging (i.e. V2G technology), has not been identified in the E-VRP literature, nor is the provision of energy arbitrage. This means that optimising EV operations is either done from the power system operation perspective, as per the power system research field, or from the EV operation perspective, as seen in the Transport Studies field. Clearly, with the electrification of transport, the power and transport systems will be much more interconnected and inter-dependent and there is currently a significant gap in this area of research. It is this precise limitation in the current literature that the present work seeks to address.

There is an emerging area of research that investigates how to coordinate charging EVs bearing in mind their transport services. To date, the use case for this approach is a shared EV fleet or an EV taxi fleet, no work has been done on the commercial maintenance or delivery fleet use case. Two such fleets from Chapter 3 are used for this purpose. In [70], historical taxi travel data and electricity prices were used to demonstrate how to maximise profits for the EV fleet owner. It was found that there was a higher demand for passenger taxi trips in the afternoon,

when electricity prices were low. During the evening peak electricity prices, it was profitable for EVs to be plugged in as they could maximise profits by discharging and selling their energy. Although the work highlights the synergies between transport demand and electricity price, ancillary service provision is not considered. Also, energy arbitrage increases battery cycling and hence degradation more than ancillary service provision. In a future low-inertia system, frequency response will become increasingly important. Ancillary service provision from EVs could reduce system costs in a future GB electricity grid by up to £12,000 a year per EV and reduce CO₂ emissions by 60 tonnes per year [71]. The authors in [72] designed a central controller for an EV taxi fleet that does include scheduling charging and discharging for ancillary service provision. The work does not schedule trips themselves, though, as this is determined by the taxi passengers. In the present work, scheduling is carried out both for trips and for charging to provide ancillary services, considering transport energy requirements and trip lengths. In summary, the main contribution of this chapter compared to previous approaches is the co-optimisation of trip schedules alongside energy and ancillary services for commercial EV fleets.

4.1.2 Motivation and Contributions

The motivation of this work is to further explore and evidence the opportunities to integrate the energy and transport systems, in order to quantify the benefits to the future power system and to EV fleet operators. It is clear that there is value in optimising charging EVs to access the flexibility, in terms of energy, they have to offer, which was demonstrated in Chapter 3. The first question this chapter addresses is how charging schedules will likely change in a low-inertia system in the future.

There also exists a body of work evidencing the value in the optimising the journeys of EVs, considering the changes to the transport system (including driving behaviour) that shifting to battery powered vehicles will have and mitigating this effect. In this chapter, which has been published [19], the author seeks to quantify the value of combining these approaches and to answer a second question, what will the value of simultaneously scheduling both EV

charging and trips be in the future power system? This is particularly interesting considering the increased penetration of renewable energy in the future and the effect on ancillary service and energy prices. Frequency response is the ancillary service modelled here, as it is of major concern for a low-inertia grid with a high penetration of renewable generation. The generation mix will radically change the time of day that ancillary services, and hence EV flexibility and availability, will be useful. As a result, the possibility of scheduling trips, in addition to charging, to account for this is what motivates this work.

As far as the author is aware, no research has sought to quantify the value of optimal trip and charging schedules of commercial EV fleets participating in ancillary service markets. This is important given the projected uptake of EVs and the opportunity they present to provide significant flexibility and reduce power system operational costs, along with other distributed energy resources [5]. This chapter seeks to consider both the fleet operation and the provision of ancillary services to the grid by optimising revenue for the commercial fleet owner considering energy and ancillary service prices. It does this by extending current approaches in optimising EV charging schedules to assess the value in scheduling trips, as well as incorporating both future prices / scenarios. This is valuable because this approach allows the fleet owners to increase their revenue, as well as the power system benefiting from an increased capacity in ancillary services. As discussed in [49], the operational costs from ancillary services is likely to increase in future power system scenarios, where more sources of renewable energy generation are present. This is an opportunity to utilise the new sources of flexibility the EVs present, while fulfilling the requirements of the EV fleet to perform its operations. Specifically, this work considers the operations of the commercial fleet, where trip lengths and distances (i.e. energy required for travel) are known, day-ahead user inputs. This work is different to existing work in that it focuses on commercial (e.g. delivery and maintenance) fleets with known transportation needs and it considers the current and future power system scenarios to demonstrate the business case for commercial EV adoption. The real world commercial data obtained has not been seen elsewhere in the literature, and given its limited volume, data was synthetically generated for the case studies, based on distributions. To the best of the author's knowledge, the main contributions of this chapter can be summarised as follows:

- Novel scheduling approach for EV fleet operators that includes both charging and trip times, generating additional revenues and exploiting synergies between the power system and road transport system
- Quantification of the value of scheduling optimal journey times accounting for frequency response prices
- Accurate characterisation of flexibility of commercial EV fleets participating in ancillary service markets
- Comprehensive assessment of revenues of commercial V1G and V2G fleets considering present and future GB scenarios with various sensitivities

It should be noted that in this work, the EVs do not perform energy arbitrage, due to the adverse impacts on the battery by increased cycle [73]. It has been found that EVs are only competitive on the electricity market, performing energy arbitrage, when the peak prices are unusually high [50]. So although the fleet will optimise its charging schedule in order to charge when the price is cheapest, it will not discharge at peak price in order to generate more revenues by selling energy. This is achieved by assuming a zero sell price for energy.

The remainder of this chapter is structured as follows; Section 4.2 provides the mathematical formulation of the problem, including the charging optimisation in Section 4.2.1, as well as the trip optimisation in Section 4.2.2. Case studies are described in Section 4.3, with the fleet data used detailed in Section 4.3.1, scenarios and prices in Section 4.2.3 and the results and discussion in Section 4.3.2. Finally, conclusions and further work are discussed in Section 4.4.

4.2 Methodology

4.2.1 Charging Schedule Optimisation

The schedule - including charging and trips - for a commercial EV fleet is optimised over a day-ahead 24-hour horizon of time steps t in total time period T . Depending on the technology (V1G

or V2G, see Section 1.2), the EV can charge (C_t) and discharge (D_t), acquiring energy needed for travel (E^{tr}), as well as providing an upward balancing service by reducing charging ($BSup_t^c$) or increasing discharging ($BSup_t^d$) in the form of availability. The charging / discharging power of an EV can be continuously regulated between 0 and a maximum power level allowed by the charger (P^{max}), and they need to fulfill a predetermined energy requirement for the scheduled journey within the interval T . The trips that the EVs of the commercial fleet need to take, including the length of the trip in hours and the energy required (i.e. the distance) is known ahead of time. This ensures that fleet operation is not affected, i.e. the fleet operator will input the trip distance and length for the EV, according to the work schedule, and the optimal start time for this trip as well as the charging schedule will be determined. The energy prices and the balancing service prices are also known ahead of the one-day time horizon, which is in line with the current wholesale energy and balancing service market arrangements.

The objective function maximises revenues from balancing services considering charging costs, while meeting the EV trip requirement for energy for travel, over the time periods that the EV is connected to the grid (T^{grid}). Smart charging takes into account the hourly import energy (buy) price π_t^b and export (sell) price π_t^s . Revenues from balancing services are from the availability of upward balancing service ($BSup_t^c$ and $BSup_t^d$) multiplied by the price (π^{BSup}), as shown in (4.1).

$$\text{maximise} \left(\sum_{t \in T^{grid}} (BSup_t^c + BSup_t^d) \cdot \pi_t^{BSup} - C_t \cdot \pi_t^b + D_t \cdot \pi_t^s \right) \quad (4.1)$$

The operating model of the EV includes several constraints. Constraint (4.2) corresponds to the EV battery's energy balance, taking into account the energy needed for travel purposes as well as the losses caused by charging and discharging efficiencies.

$$E_t = E_{t-1} + C_t \Delta t \eta_c - \frac{D_t \Delta t}{\eta_d} - E^{tr}, \forall t \in T \quad (4.2)$$

Each EV is assumed to depart from its grid connection point up to once within the time horizon

and subsequently arrive back to its grid connection point only once during the same horizon. This is in line with the trend clearly seen in the real world data, whereby the commercial vehicles follow a schedule of one extended trip from the depot in one day. Outside of this single trip, the EVs are otherwise assumed to be connected to the grid, the hours of which constitute the time period T^{grid} . When the EVs are not connected to the grid, the charging, discharging and balancing services are zero, as per constraint (4.3).

$$C_t = D_t = BSup_t^c = BSup_t^d = 0, \forall t \notin T^{grid} \quad (4.3)$$

Constraint (4.4) expresses the lower (E^{min}) and upper (E^{max}) bounds of the battery's energy content, assumed to be the same for each EV.

$$E^{min} \leq E_t \leq E^{max}, \forall t \in T \quad (4.4)$$

Constraint (4.5) ensures that the energy level of the EV at the start of the trip ($E_{t_{start}}$) is at the required level (E^{req}) set by the fleet operator, in order to ensure the EV can carry out its work trip.

$$E_{t_{start}} = E^{req} \quad (4.5)$$

Constraints (4.6) and (4.7) represent the limits of the battery's charging / discharging power, which depend on its power capacity P^{max} and on the availability of the EV to be scheduled (i.e. time period connected to the grid, T^{grid}). The binary variable y ensures that charging and discharging do not happen simultaneously.

$$C_t \leq y \cdot P^{max}, \forall t \in T^{grid} \quad (4.6)$$

$$D_t \leq (1 - y) \cdot P^{max}, \forall t \in T^{grid} \quad (4.7)$$

Constraints (4.8 - (4.10)) ensure that the balancing service availability committed takes into account the maximum power of the charger and whether the EV is charging or discharging.

$$BSup_t^d + D_t \leq P^{max}, \forall t \in T^{grid} \quad (4.8)$$

$$BSup_t^c \leq C_t, \forall t \in T^{grid} \quad (4.9)$$

$$(D_t - C_t) + (BSup_t^c + BSup_t^d) \leq P^{max}, \forall t \in T^{grid} \quad (4.10)$$

When committing balancing service availability, it is important to ensure that the energy is available for the service to be sustained for the minimum required time (t_s) if this service was called on. This applies to the balancing service from discharging ($BSup_t^d$) in particular, due to this being an upward balancing service. This is captured in constraints (4.12) - (4.14) by considering the state of charge of the battery at the beginning and at the end of the time step. The balancing service provision from EVs only considers availability, rather than utilisation, which is assumed to occur infrequently [13].

$$E^{min} \leq \min(E_t, E_{t-1}) - \frac{BSup_t^d \cdot t_s}{\eta_d}, \forall t \in T^{grid} \quad (4.11)$$

The above constraint can be linearised by introducing an auxiliary decision variable ' x_1 ' and two additional constraints:

$$E^{min} \leq x_1 - \frac{BSup_t^d \cdot t_s}{\eta_d}, \forall t \in T^{grid} \quad (4.12)$$

$$x_1 \leq E_t \quad (4.13)$$

$$x_1 \leq E_{t-1} \quad (4.14)$$

4.2.2 Trip Schedule Optimisation

The optimal trip start time (t_{start}^*) is found by maximising the revenue from the EV, according to the optimal charging schedule in Section 4.2.1, across different feasible start times t_{start} in which the EV could make the trip required. The variable t_{start} informs when the EV is connected to the grid (T^{grid} in (4.1)) and able to charge, discharge or provide frequency response. Therefore, a different optimal revenue corresponds to each t_{start} . To make the notation easier, the objective function in Eq. 4.1 is defined as $\beta(t_{start})$.

The time that the trip is able to start is constrained by how long the trip is (T^{trip}), as well as the permissible travel window (T^{window}). For instance, if the 24-hour period starts at 7am with a trip required lasting five hours and a window of 15 hours (i.e. the EV can be away from the charger between 7am and 9pm), the start time could be any hour from 7am to 4pm. The trip schedule optimisation problem is formulated as follows:

$$\begin{aligned}
 & \underset{t_{start}}{\text{maximise}} && \beta(t_{start}) \\
 & \text{subject to} && t_{start} < T^{window} - T^{trip} \\
 & && T^{grid} = T - (t_{start} + T^{trip})
 \end{aligned} \tag{4.15}$$

It is important to note that although the assumption is the trip length will remain the same regardless of the time of day it is taken, there is a level of uncertainty related to external factors, such as road blockages and traffic levels. Although in practice the fleet operator needs to create a schedule for the next day (hence the decision to formulate the scheduling problem here as such), there may be some flexibility by one or two hours on the day, to account for these uncertainties. For example, if there is a road blockage and the trip could be delayed by one or two hours. To investigate the effects of these external factors, a sensitivity analysis has been performed in Section 4.3.5.

Figure 4.1 shows an overview of the workflow of the above methodology, producing a quantification of the value from the optimal trip and scheduling approach. Table 4.1 lists the input

and decision variables used, including from the fleet operator and from the market.

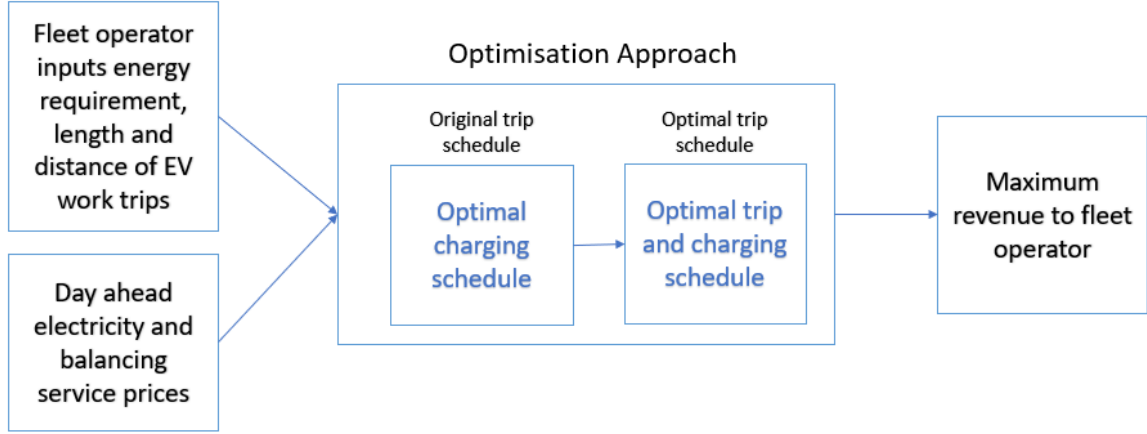


Figure 4.1: Summary of workflow.

Table 4.1: Summary of Variables Used in Optimisation Approach

	Input Parameters	Decision Variables
Fleet Operator	$E^{tr}, E^{req}, T^{trip}$	t_{start}, C_t, D_t
Market Information	$\pi_t^{BSup}, \pi_t^b, \pi_t^s$	$BSup_t^c, BSup_t^d$

4.2.3 EV Operation and Scenario Specific Constraints

In order to assess the value of the approach presented in this work, different scenarios representing different modes of operation are modelled. This allows for insights into the various business cases for commercial EV adoption. EVs can operate in various modes, including dumb charging, smart charging and V2G. Here, the scenarios applied are described, along with a description of the state of pricing and price assumptions. In all scenarios, a zero sell price for energy is assumed, so although the EVs can discharge to the grid, energy arbitrage is not profitable. This is because the focus of this chapter is the provision of upward balancing services from commercial EV fleets and energy arbitrage will potentially degrade the battery by increasing the number of charge cycles [73].

The first scenario, which is the baseline, is the ‘dumb charging’ scenario. Here, EVs plug in and charge back up to their desired value (in this case 95% SOC) immediately, regardless of the price of energy on return. Also, the scenario specific constraints include (4.16) and (4.17), shown

below. This modification to original constraints (4.7), (4.8) and (4.9) allows a comparison to the current uni-directional charger costs as these new constraints stop the EVs from being able to discharge and provide upward balancing services (i.e. frequency response services). For this scenario, introducing a flexible trip start time is comparable to moving the charging event itself. The only difference is the window of travel (i.e. when the EVs may perform journeys) is more limited than the full 24 hours or available plug in times.

The prices used for summer and winter months are based on July 2019 and February 2020 wholesale electricity market prices in GB, respectively, in order to remove the distortion brought about by the Covid-19 pandemic. The timing of these prices was chosen to align with the months from which the travel data was collected, as described in Section 4.3.1.

$$D_t = 0, \forall t \in T^{gr} \quad (4.16)$$

$$BSup_t^c = BSup_t^d = 0, \forall t \in T^{gr} \quad (4.17)$$

The second scenario is the smart charging scenario, where EVs charge at times when the cost of energy is lowest. The effect of moving the trip times in this case would only improve revenue if the original trips occurred when the price of energy is at the lowest point in the day. The modification of the original constraints is the same as for dumb charging, as shown in (4.16) and (4.17).

The third scenario is the newest frequency response product on the GB market at the time of writing, Dynamic Containment [38], which represents the current state of the market. The prices reflect the value of frequency response at present, in markets which are constantly changing and being updated. When the newest frequency product was launched, it was the first day-ahead procured response product but had a constant price throughout each day. The prices of this product in this scenario are therefore assumed to be constant [39], something that does not reflect the value of balancing the system and the time-varying requirement for frequency

response products. This is because when system inertia is low, i.e. renewable energy on the system is high and therefore net demand is low, the value of frequency response is significantly higher than in high-inertia conditions [74]. Nonetheless, the prices seen in the Dynamic Containment market so far are higher than for previous fast frequency response products, such as Enhanced Frequency Response, which was procured through years-long contracts [75]. Trends show that the prices of frequency response have increased over time.

The fourth and final scenario is the future frequency response scenario. Here, the price of frequency response is a reflection of the value of this service to a future system. The methodology by which these prices were generated is described in Section 4.2.4 below.

4.2.4 Modelling Future Frequency Response Prices in Great Britain

A view of future prices for the fast frequency response service in GB (referred to as Dynamic Containment, DC) was produced using a different model and used here as inputs. This was done with a view to estimate the potential revenue from EVs with V2G capability. To produce this view, a different, frequency-constrained model was used, which outputs the projected price for DC for a given hour, based on the need for this service under each system condition (i.e. level of demand and generation mix). This model was not the author's work but was included in the paper published that forms the basis of this chapter. How the prices were generated is summarised here, in order to be clear about assumptions made.

A demand curve with seasonal and daily trends was used, consistent with National Grid's projections for 2030 [76], ranging from 20 GW to 60 GW of instantaneous hourly demand. A total of 45 GW of onshore and offshore wind combined was assumed, along with 35 GW of solar PV. A nuclear capacity of 5 GW was assumed, also in line with [76]. Given these system characteristics, the frequency response price for each hour of the future frequency response scenario / product is computed as follows:

1. Net-demand is obtained by subtracting RES generation from national demand. The level of inertia in the system is estimated by considering that net-demand is covered by nuclear

units (5GW with a 5s inertia constants) and Combined-Cycle Gas Turbines with an inertia constant of 5s.

2. If the level of inertia obtained in Step 1 is below the minimum acceptable value for this magnitude, inertia is fixed at this minimum. This ‘floor’ for inertia is determined by the Rate-of-Change-of-Frequency (RoCoF) limit, as defined by the expression below. Please refer to [74] for full details on the impact of inertia on RoCoF.

$$H_{\text{floor}} = \frac{P_{\text{infeed}} \cdot f_0}{2 \cdot \text{RoCoF}_{\text{limit}}} \quad (4.18)$$

In (4.18), H_{floor} is the floor for inertia, P_{infeed} is the largest power infeed in the national system (considered to be 1.8GW), f_0 is the nominal frequency of the grid (50Hz in GB) and $\text{RoCoF}_{\text{limit}}$ is the RoCoF limit (of 1Hz/s in the future GB system).

3. Given the level of inertia obtained from Steps 1 and 2, the necessary volume of Primary Frequency Response (PFR) for this system condition is computed. Note that PFR refers to the slower frequency response provided by electromechanical devices, such as synchronous generators. To compute this necessary volume of PFR, the system condition for respecting that the frequency nadir will not cause the activation of Under-Frequency Load Shedding is used [77]. This condition guarantees that frequency stability will be maintained in the system, and therefore defines the requirement for ancillary services: it defines the required balance between volumes of inertia, size of the largest power infeed, and the two frequency response services, in order to avoid Under-Frequency Load Shedding. The interested reader is referred to [77] for full details on how this constraint is deduced.
4. Given that the value of all magnitudes in the condition in Step 3 is defined, except that of PFR, this unknown can be directly solved. The volume of DC is considered to be of 1 GW (as per current plans in Great Britain [49]) and the size of the largest power infeed is of 1.8 GW (driven by a nuclear station expected to be commissioned in GB in the coming years).

5. Finally, the price of DC is computed from the volume of PFR that an additional MW of DC could replace, obtained from the condition in Step 3. A price of £10/MW/h for PFR was considered, in line with average prices seen for this service in GB in recent years [78].

A sensitivity analysis on these projected prices is considered in Section 4.3.4, to provide a comprehensive view on V2G revenues under different scenarios for future prices for Dynamic Containment.

4.3 Case Studies

This section details the inputs and the results for several case studies chosen in a way as to be closest to real world future scenarios and to demonstrate the value of the approach. Section 4.3.1 describes the input fleet data, including trends of driving patterns of two fleet types. The approach to generate synthetic data based on these trends is also included. Section 4.3.2 presents the results from the various operational scenarios described in Section 4.2.3. Then, the technique applied to reduce battery cycling in the modelling is described in Section 4.3.3. Results of sensitivity analysis, key to understanding how susceptible the revenues derived are to changes in frequency response price and traffic conditions, are shown in Section 4.3.4 and Section 4.3.5, respectively. Finally, the consequence of the given approach on CO₂ emissions is quantified in Section 4.3.6.

4.3.1 Fleet Data

Derived from the Innovate UK funded project E-Flex [15], the driving patterns from two commercial fleets participating in the trial were analysed and synthetic data was generated. Two types of commercial fleets were considered: i) a delivery fleet with 10 EVs; and ii) a maintenance fleet with 5 EVs. The reason that these fleets were chosen in that commercial fleets have regular, defined trips that are scheduled during weekdays. Compared to private vehicles,

commercial fleets are well suited to balancing service provision with V2G due to their coordination by fleet operators, making them easier to aggregate. The main differences between the two fleets are summarised in Table 4.2 for winter and summer months. For the delivery fleet, although the mean travel duration and trip length range increase in the summer compared to the winter, the mean travel energy decreases. The opposite is true for the maintenance fleet, which has a higher mean travel energy in the summer compared to winter, but a shorter mean travel duration. The difference between winter and summer for the maintenance fleet and its implications are discussed in Section 4.3.2. The differences between the fleet types are examined in Section 4.3.2.

Table 4.2: The Characteristics of the Two Commercial Fleets in Winter and Summer Months

	Winter		Summer	
	Delivery	Maintenance	Delivery	Maintenance
Travel start time mean	10.30am	8.00am	7.30am	8.00am
Charging start time mean	2.30pm	3.00pm	1.30pm	12.00pm
Travel duration mean	5h	7.5h	6.5h	6.5h
Travel duration min & max	0.5h – 6h	7h – 8h	0.5h – 9h	5h – 8h
Travel energy mean	8.9kWh	4.2kWh	7.7kWh	5.7kWh

The 24-hour driving patterns $x(t)$ of the commercial fleets showed $x(t) = -1$ for time steps t when the EV was connected to the grid and $x(t) = 0$ for time steps t when the EV was on a trip. The energy needed for travel at the first time step was t_{return} . The EV was connected to the grid again following the trip. Values of $x(t) < 0$ do not indicate any energy exchanges, e.g. energy feeding into the grid, but only that the EV is not on a trip. Two months were chosen to be representative of winter and summer months, i.e. February and July respectively. For each of these two months, the driving patterns for each of the two commercial fleets were fitted with the Gaussian function defined in Equation 4.19 [51], [59].

$$f(x(t)) = a \cdot \exp \left(-\frac{(x(t) - b)^2}{c^2} \right) \quad \forall t \in [0, T] \quad (4.19)$$

In Equation 4.19 a is the height of the curve's peak, b is the position of the center of the peak, and c is the Gaussian width. These parameters were then optimised to improve the fitness of

the function to the real patterns using non-linear least squares analysis, resulting in residual standard deviations less than one. The fitting function for the month of July of the maintenance fleet is shown in Figure 4.2. The height of the curve's peak is relatively low as most of the hours the EVs were connected to the grid or on a trip. Once the optimal fitting curve was obtained, the parameters $a \in [0, \max\{x(t)\}]$ and $b \in \{t | f(x(t)) > 0\}$ were randomly sampled to generate synthetic driving patterns. The parameter c was not varied as it defines the length of the trip that is distinctive for each fleet. The 24-hour driving patterns of 100 EVs for each of the two fleets were finally generated for the months of February and July.

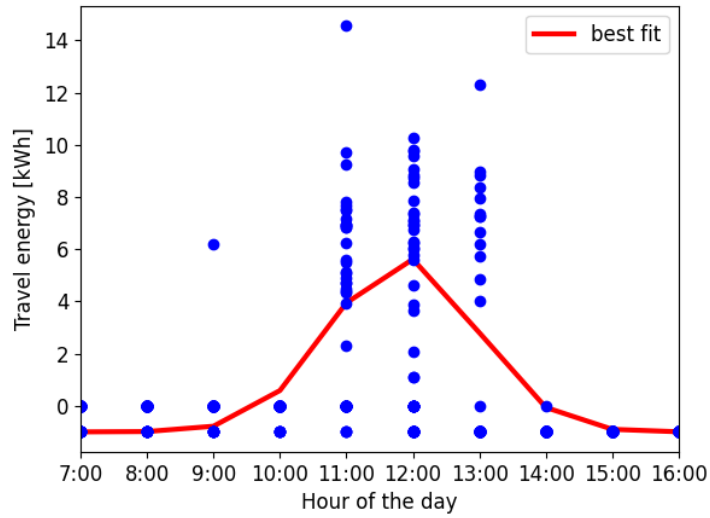


Figure 4.2: The driving patterns distribution for the month of July of the maintenance fleet and the optimised fitting function in red.

4.3.2 Results and Discussion

Following the details of the case studies set out in Section 4.3, the results from the case studies are presented and findings are discussed here. The results make a comparison between both the summer and winter seasons, showing the effects of renewable generation on ancillary services prices and hence revenue. The revenues for the inflexible (i.e. original) trips and the flexible trips across the summer and winter seasons were first compared using the maintenance fleet to model the four scenarios outlined in Section 4.2.3. Then, the difference between the maintenance and delivery fleets was investigated to show how driving patterns affect revenue in this approach.

Lastly, some extreme weather days were analysed to show examples of potential maximum benefit from flexible trips. This is a way to demonstrate the major differences between fleets and seasons in an extreme case.

The optimisation problem defined in Section 4.2 was modelled in Python using the Gurobi Python Environment, with a MIP gap of 0.1%. It was run on a machine with a 3.6GHz Intel Core i7-7820X 8-Core processor and 64 GB of RAM. The average computing time was 20 minutes.

Optimal Start Times in Different Months for Maintenance Fleet

Using the fleet data described in Section 4.3.1, the four scenarios were simulated for both the summer and winter months with the original start time of the trips, then with optimal trips. The maintenance fleet results are shown in Figure 4.3. The dumb charging scenario of the maintenance fleet shows that the charging costs (i.e. energy costs for travel) are higher in the summer, due to further distances travelled (see Table 4.2) and higher electricity prices (as described in Section 4.2.3). By making the timing of the journeys flexible, there is a maximum cost saving of 38% in the winter month for this scenario, relative to the original travel pattern, compared to the cost saving of 12% in the summer. This means when charging on arrival in the winter, there is relatively more benefit in moving this plug in time (by moving the trip) in order to capture lower energy prices and reduce costs. Averaging this benefit over a whole year, a single EV from the maintenance fleet can make an additional annual revenue of up to £729 by incorporating flexible journeys into its operations.

Changing the trip times in the smart charging scenario does not save on costs because the charging will occur at night in either case, when the prices are lowest and when the EVs are connected.

By adding bidirectional (V2G) charging, the EVs are now able to participate in the frequency response market, resulting in positive net revenues for the third and fourth scenarios. In the third scenario, having flexible start times does not generate a significant increase in revenue, due to the fact that current frequency response prices used are constant for every hour in the

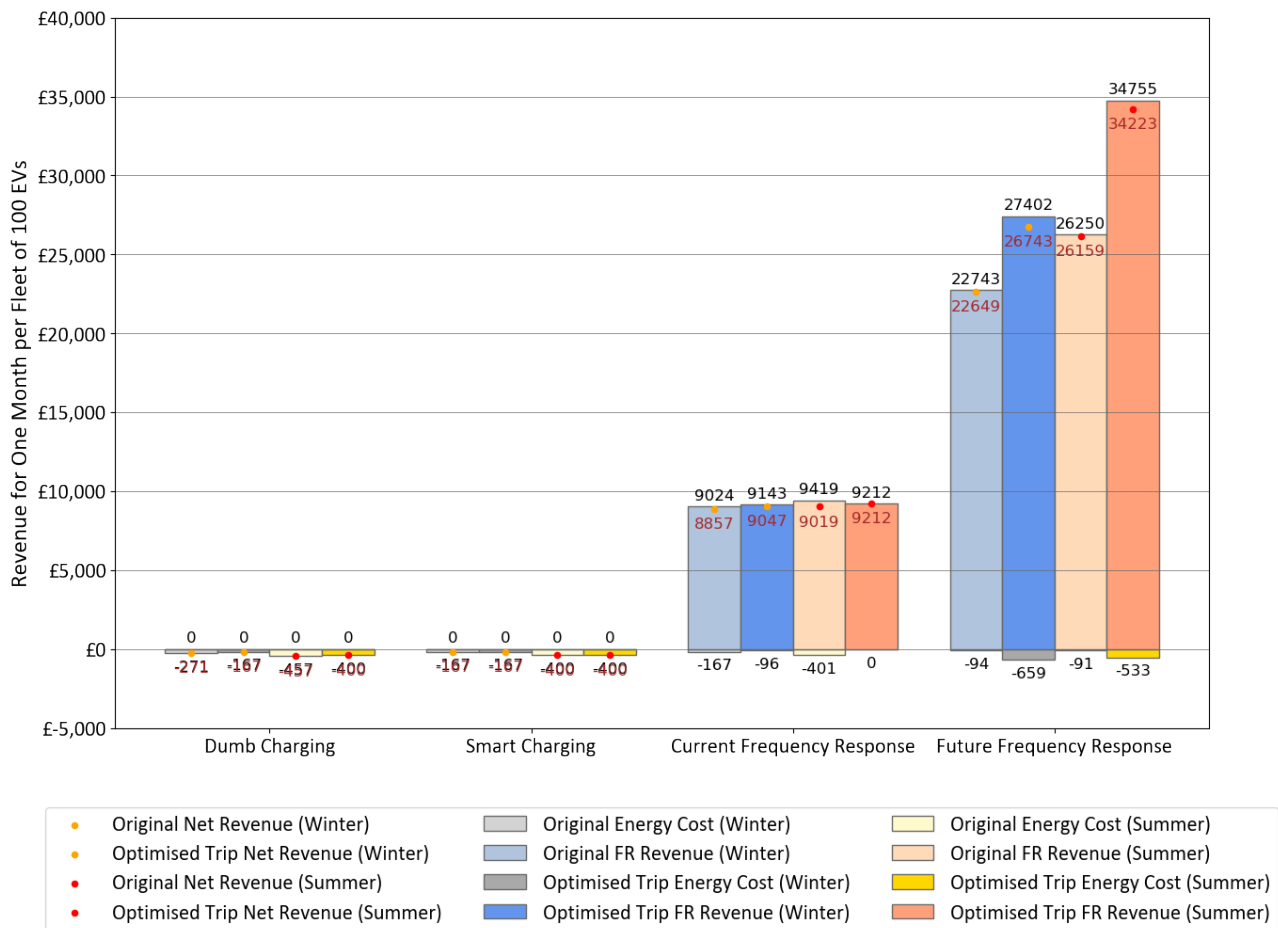


Figure 4.3: Summer and Winter Months for Maintenance Fleet with and without Optimal Trip Scheduling

day.

By avoiding traveling in times of high future frequency response prices, optimal trip scheduling allows for more revenue from this service in both months of the fourth scenario. The energy costs also reduce with optimal trips, due to the flexibility of the start time, where batteries must be charged to the required level. An assumption is made that when scheduling flexible trips, the 24-hour period begins with a 50% state of charge (or the maximum state of charge in order for the EV to depart with the 95% requirement).

It is also worth noting that the energy costs increase in the fourth scenario due to the fact that it is beneficial to charge at time periods of high frequency response prices. When charging, the EV will get paid for offering availability to reduce its charging and increase its discharging, i.e. as per objective function (4.1). As the EVs are plugged in when frequency response prices are higher, they will charge at these times, and although they will be charged for the energy, this still results in a net revenue that is higher than the original trip times.

In the future frequency response scenario, fleet revenues are expected to rise by 156% in the winter and 190% in the summer with original trips or driving patterns, as compared to the current frequency response scenario. When trip start times are optimised in this scenario, the revenues increase by 18% in the winter and 31% in the summer, as compared to the same scenario with original trip times. As described in Section 4.2.4, the frequency response prices depend on net demand, which in turn depends on renewable energy generation. The reason why introducing optimal start times results in a larger improvement in the summer month is that solar output occurs during the day, driving up the price of frequency response. The maintenance fleets are able to use this to their benefit and schedule their trips for later in the day, in order to maximise revenue by remaining plugged in at these times in order to provide frequency response services. In the winter, the dominant renewable generation is wind, which is usually strongest at night, when fleets are not typically operational. An example of this seasonal difference is shown in Figure 4.4, where two days of frequency response prices show a regular pattern in the summer month. The original trip times occur during peak frequency response prices and benefit from being moved to later in the day, when frequency response

prices are lower. In the winter, however, wind and hence prices do not follow such a regular pattern. Although during the first day of winter in this example, it is beneficial to move the trip to later in the day, for the second winter day it is best to travel as originally scheduled.

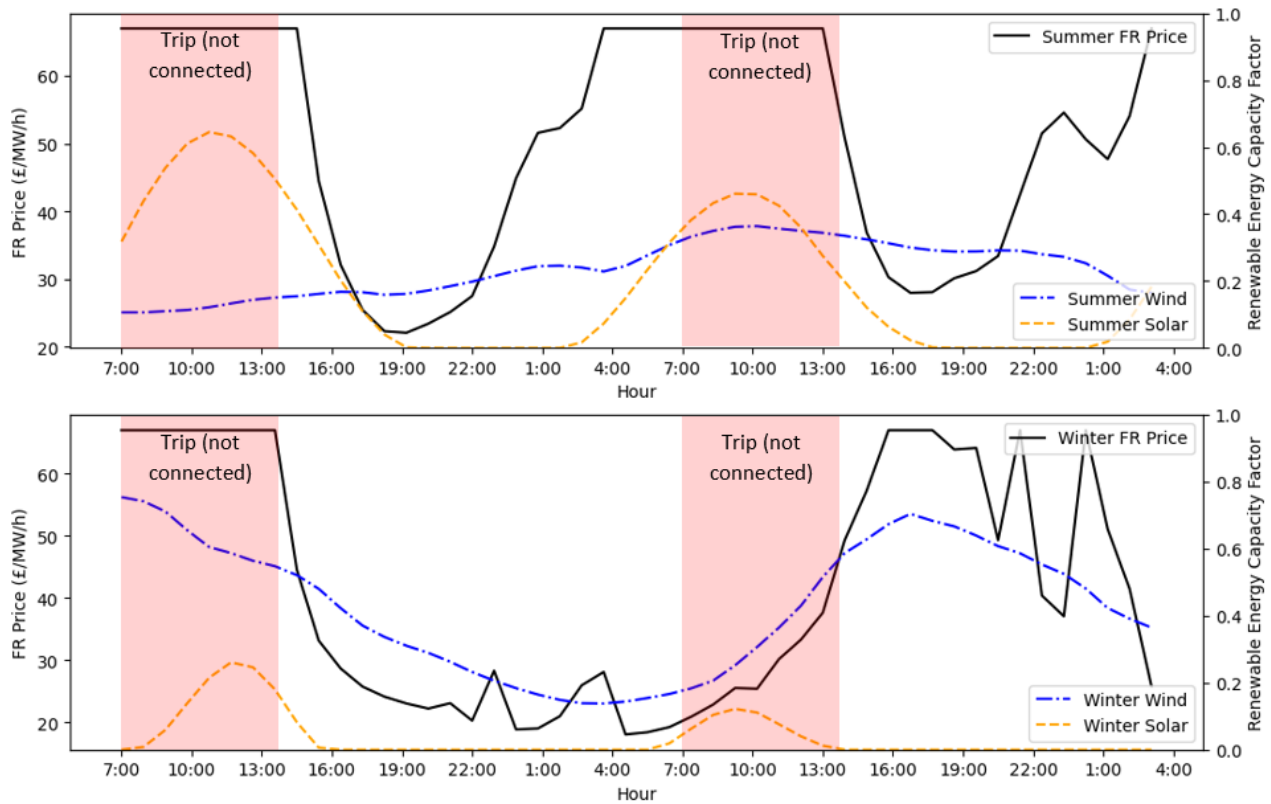


Figure 4.4: Example Summer and Winter Days Comparison

Optimal Start Times in Summer Month for Maintenance and Delivery Fleets

In Figure 4.5, the delivery fleet data is introduced in comparison to the maintenance fleet in the summer month, in order to understand the effect of fleet type on revenues. As shown in Table 4.2, the mean travel duration is the same for these fleets, but the delivery fleet will travel further, using more energy. Also, the maintenance fleet makes more consistent journeys, all between five and eight hours long, whereas the delivery fleet has a much shorter minimum journey length and a longer maximum journey length. In addition to a different travel pattern, the windows in which the fleets are assumed to travel within are different. With flexible start times, the maintenance fleet is able to travel in a 22 hour window, so from 7am to 5am, allowing time to return to base and charge before the next day. When planning fleet logistics, the delivery fleet will likely have more limitations in terms of when its trips can be made, and so the travel

window is set to 16 hours, between 7am and 11pm.

In the current frequency response scenario, revenues from optimising trip times are similar compared to the original trips, as frequency response prices are static throughout the 24-hour period. The maintenance fleet has slightly more revenue, as the trips have a lower mean travel energy. However, in the future frequency response scenario, the maintenance fleet has a higher increase in revenue from flexible journeys of 31% compared to the delivery fleet of 28%. This is because the original trips made by the maintenance fleet were consistently longer than the delivery fleet, so a greater percentage of the trips would benefit from having a flexible start time, capturing revenues from providing frequency response by shifting the journey later in the day.

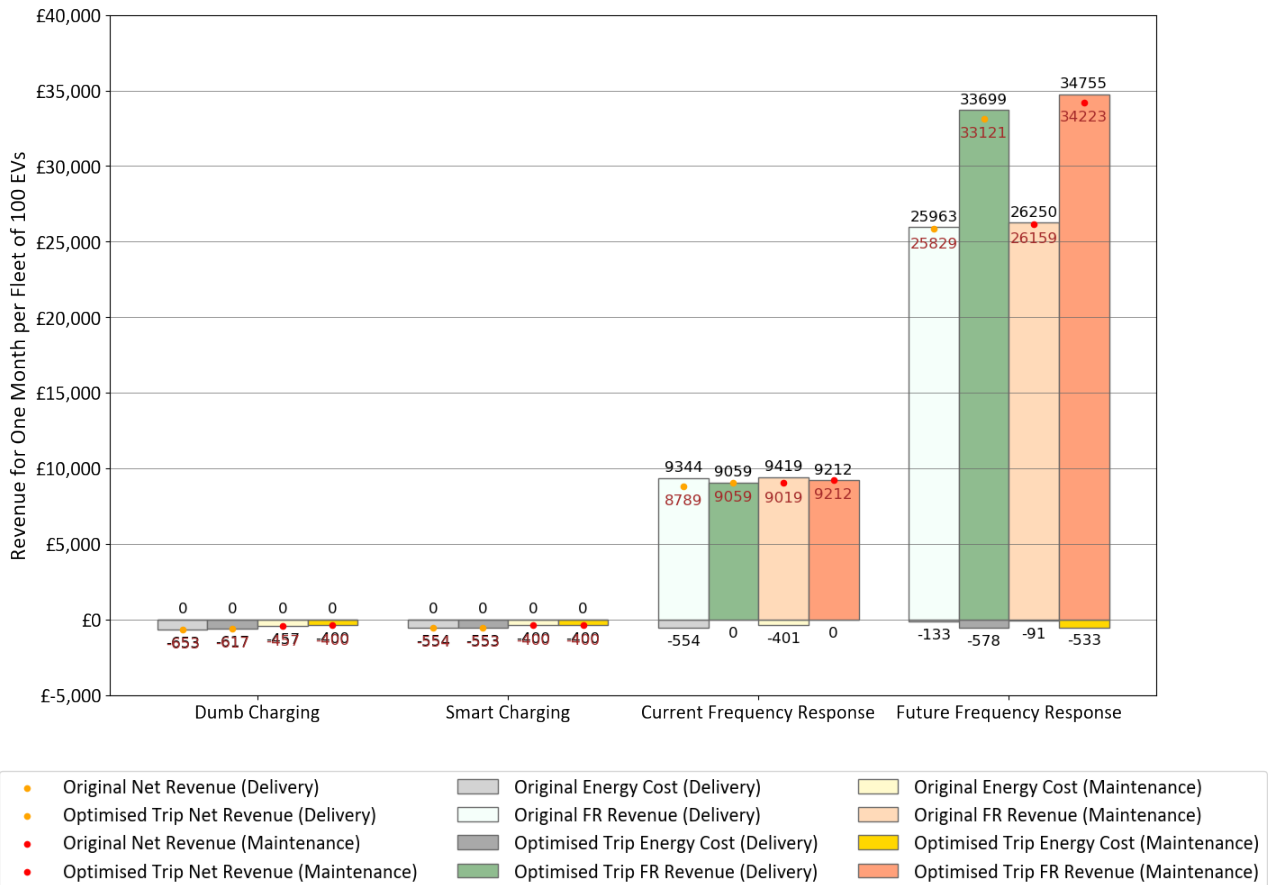


Figure 4.5: Comparison of Delivery and Maintenance Fleets in Summer Month with and without Optimal Trip Scheduling

Optimal Start Times on Future Extreme Weather Days for Maintenance and Delivery Fleets

Assuming that in the future, prices of frequency response products will reflect net demand and hence system inertia, some extreme weather days (i.e. days with the most favourable weather conditions for increasing revenues through flexible journeys) have been simulated to investigate the maximum potential benefit of flexible trip scheduling. In Figure 4.6, revenues during an extreme winter and summer day are shown for both fleets. The summer scenario demonstrates more benefit from optimal trip scheduling, with the maintenance fleet and delivery fleet increasing their revenues by 135% and 140% respectively, compared to original trip schedules. This is due to how valuable frequency response will be during daylight hours on days where solar generation is high and net demand is low.

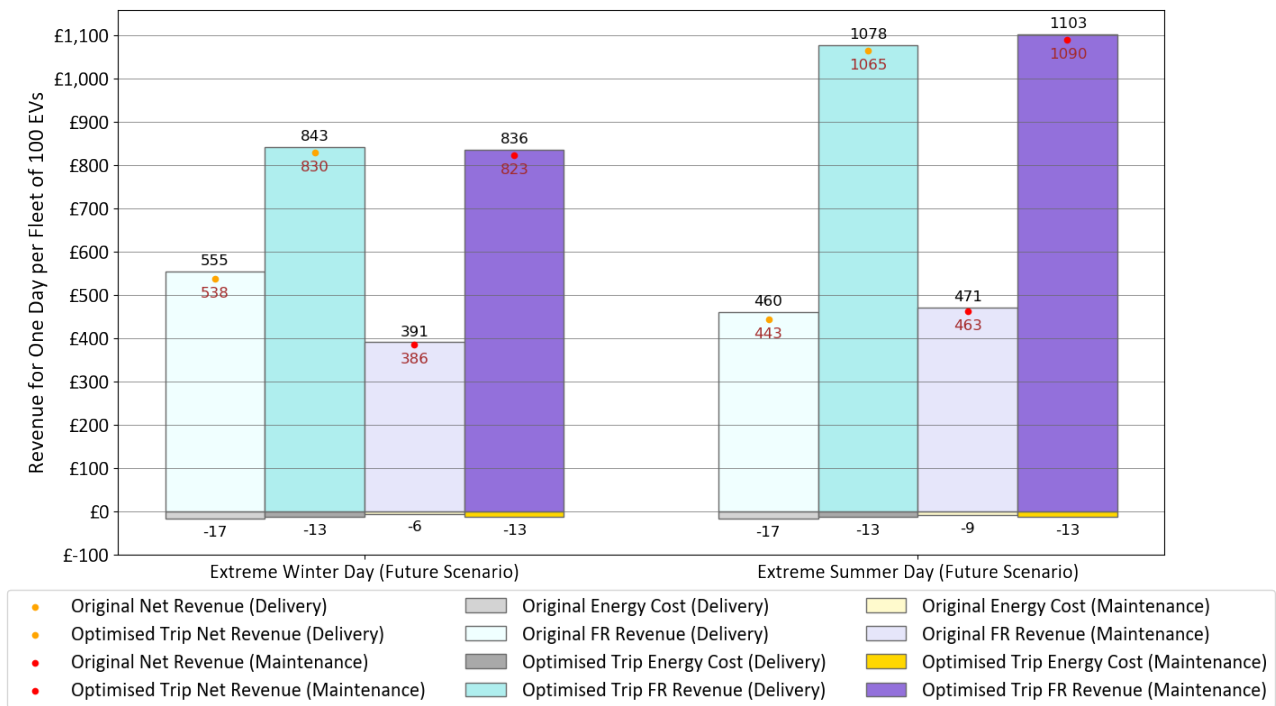


Figure 4.6: Extreme Summer and Winter Days for Delivery and Maintenance Fleets with and without Optimal Trip Scheduling in Future Scenario

Figure 4.7 shows an example of an original trip schedule over a 24-hour period for a maintenance fleet vehicle on an extreme summer day. As the vehicle is on a trip from 7am to 1pm, it is not able to offer frequency response when the prices are high. In Figure 4.8, the trip has been optimised and starts in the afternoon, when frequency response prices are lowest. In this way,

the EV can provide maximum frequency response earlier in the day by staying plugged in and delaying its journey.

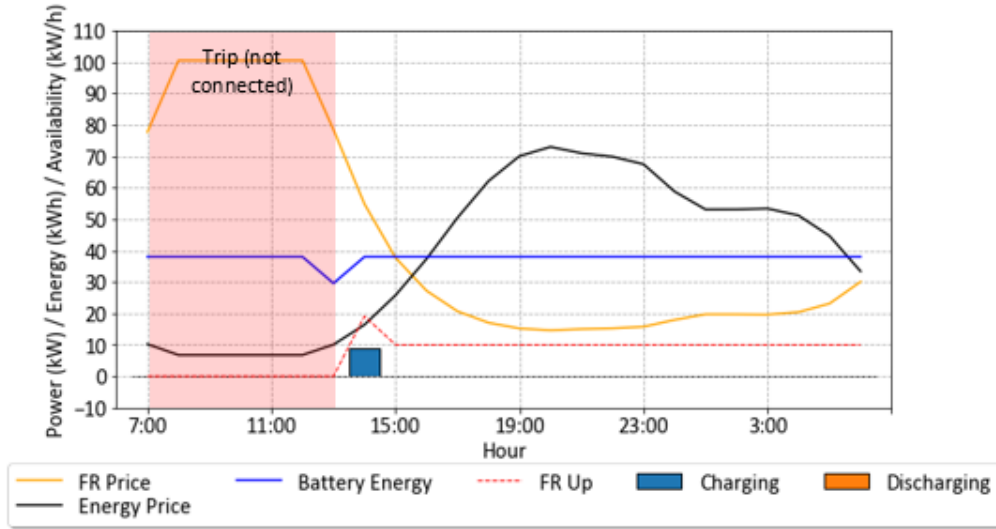


Figure 4.7: Extreme Summer Day: Original Trip by Maintenance Fleet Vehicle

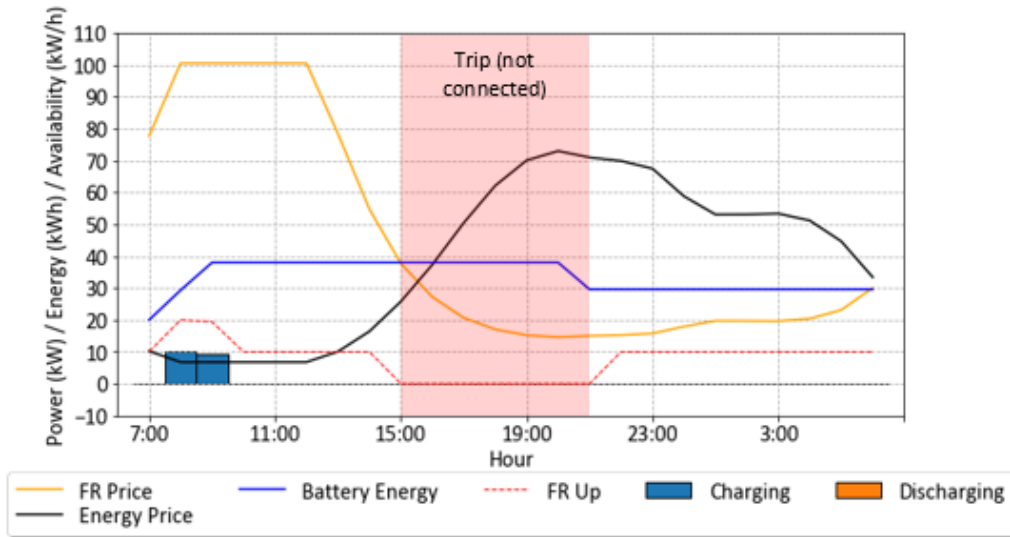


Figure 4.8: Extreme Summer Day: Optimal Trip by Maintenance Fleet Vehicle

4.3.3 Method to Reduce Battery Cycling

When prices for frequency response are high, the optimal charging behaviour of the EVs involves ‘cycling’ (i.e. charging then discharging) in order to increase revenues, as shown in Figure 4.9. This is profitable for the EV if charging and discharging efficiencies are considered, otherwise providing two time periods of charging fully and then discharging would be equal to two time

periods of neither charging or discharging. Due to losses associated with efficiencies, energy is dissipated, allowing for the EV battery to commit to more in availability than it acquires in energy. This effect leads to repeated cycles of battery charging-discharging to increase frequency response revenues.

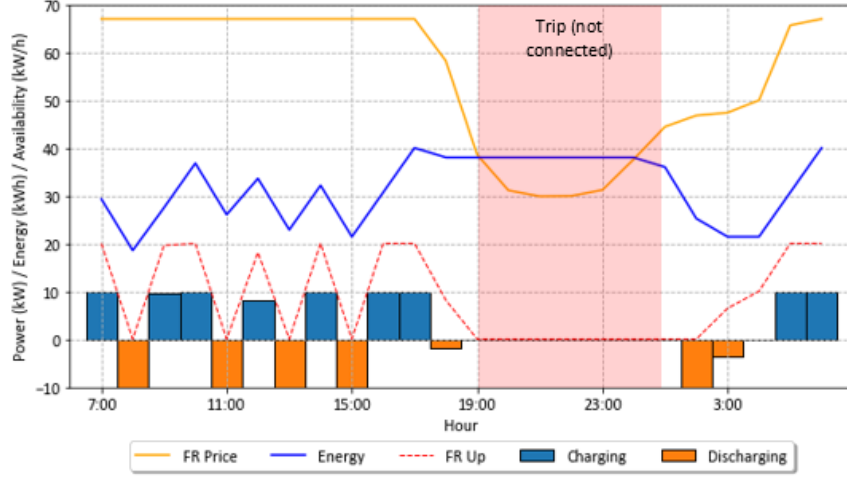


Figure 4.9: Summer Day: Optimal Trip by Maintenance Fleet Vehicle

As this unintended effect has a detrimental impact on battery health [73], a penalty term (δ) was applied to the discharging term (D_t) in (4.20). By applying a penalty to discharging, this minimises battery cycling, while only minimally affecting revenues from providing frequency response availability. This is shown in Figure 4.10 for the same summer scenario. This reduces revenues in this case by 3%.

$$\text{maximise} \left(\sum_{t \in T^{grid}} (BSup_t^c + BSup_t^d) \cdot \pi_t^{BSup} - C_t \cdot \pi_t^b - D_t \cdot \pi_t^s \cdot \delta \right) \quad (4.20)$$

The appropriate value for the penalty ‘ δ ’ depends on the maximum frequency response prices that may be captured by the EV: the penalty must be sufficiently high as to avoid the revenue gains from cycling. In this chapter, the value used was $\delta = 0.5$.

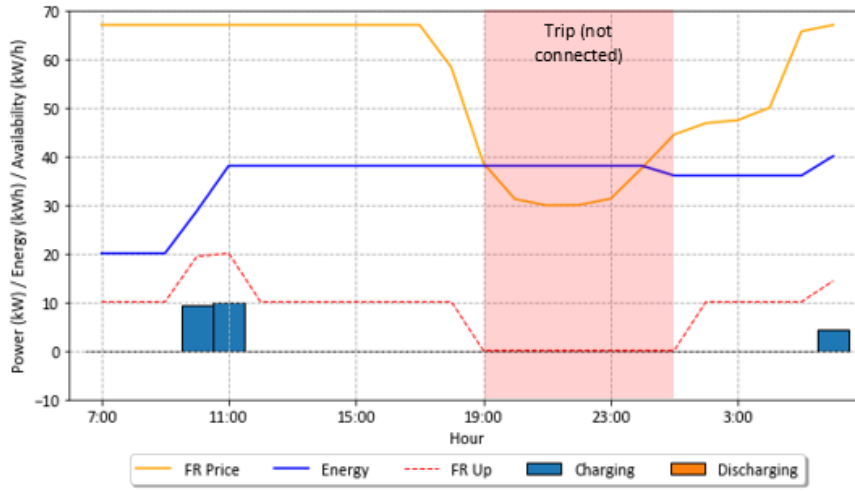


Figure 4.10: Summer Day: Optimal Trip by Maintenance Fleet Vehicle with Penalty Applied

4.3.4 Sensitivity Analysis: Frequency Response Prices

In order to demonstrate how sensitive the revenues for these fleets were to future frequency response prices (see Section 4.2.4), sensitivity analysis was performed for three scenarios, as shown in Figure 4.11. The way this analysis was performed was to run the original optimisation, bench-marked against the same prices but no optimal trips (as in Section 4.3.2), first with the full future frequency response price (100%). The frequency response price was then reduced to 75% and then 50%, in order to see the impact on revenues that a reduced price would have. This is a way to investigate the uncertainty of these prices.

Based on the results of the sensitivity analysis, the resulting increased revenues of flexible trips compared to original trip schedules is consistently around 23%. Meaning, the additional revenue gained from scheduling trips is proportionally the same, regardless of the frequency response prices. In other words, the price does not change how much added value the approach brings. A 25% reduction in frequency response price led to a similar subsequent reduction in revenue (for both original and optimal trip schedules) of 25%. However, a reduction of the frequency response price by another 25% led to a greater reduction in revenues of 33% - 34%, relative to the 75% case.

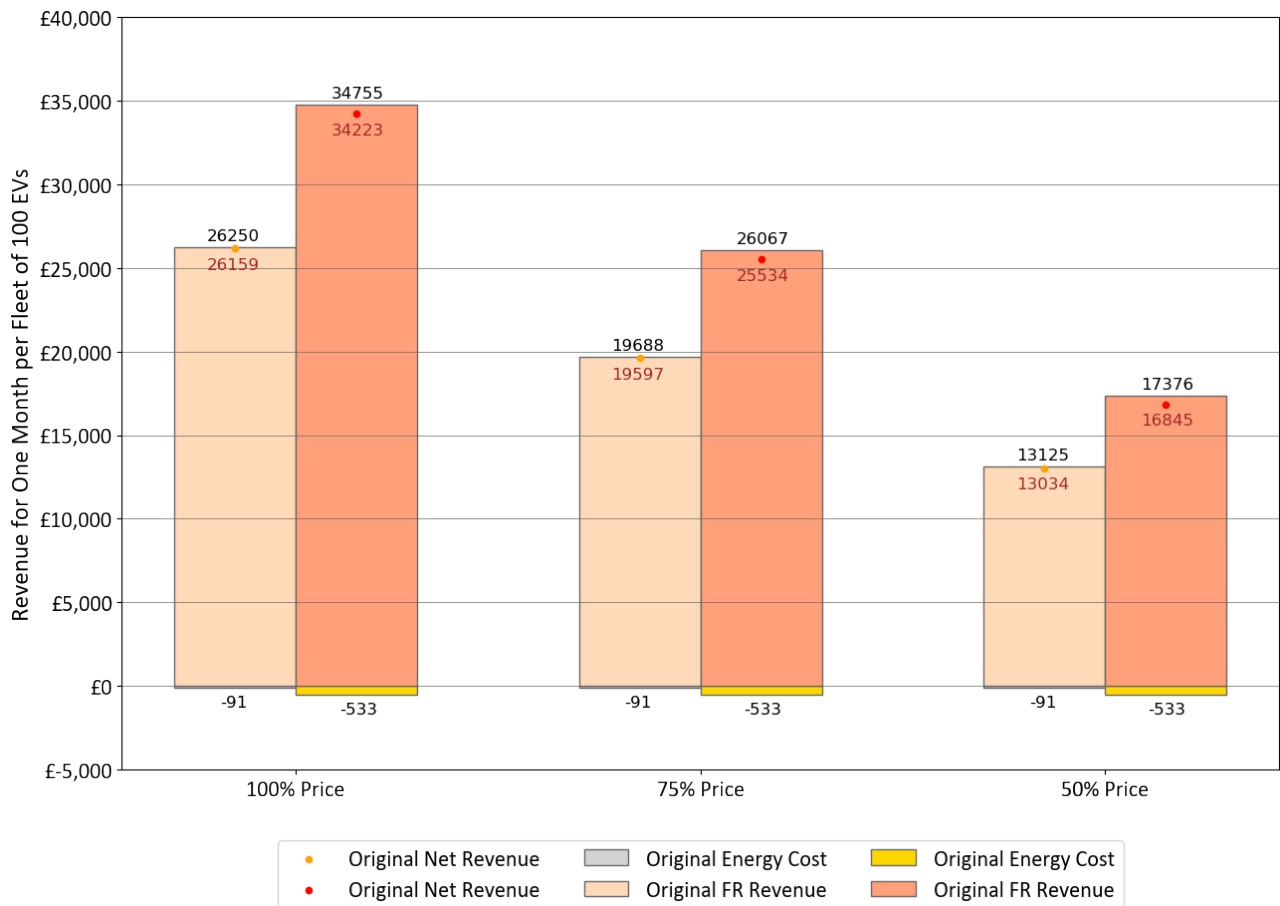


Figure 4.11: Sensitivity Analysis of Maintenance Fleet Summer Revenues under 3 DC Price Scenarios

4.3.5 Sensitivity Analysis: Traffic-Related Factors

It is recognised that there is a degree of uncertainty around trip length. It could be that trip length is affected by external factors including road blockages and traffic conditions. This uncertainty in trip length is explored by performing a sensitivity analysis to understand the impact of such factors on the revenue and hence the usefulness of the approach, particularly in areas where external factors are likely to impact trip length. These include cities, for example, where commercial fleets are likely to operate.

As shown in Figure 4.12, it was found that for the maintenance fleet, maximum revenues attainable with optimal trips in the summer were reduced by 7% by extending the trip length by one hour and by 11% by extending the trip length by two hours. For the same fleet, in the winter, maximum revenues were reduced by 8% by extending the trip length by one hour and by 13% by extending the trip length by two hours.

The reason the EV fleet loses more revenue as a result of a longer trip delay in the winter is similar to the reasons less revenue was added by flexible trip times in Section 4.3.2. During winter, there is more price variability and less regular daily weather patterns dominated by solar generation (as in the summer). If the trip were to be delayed to the evening on some days where wind was increasing as the day went on and FR prices were increasing, then the EV fleet revenue will be more susceptible to being impacted by longer trips (i.e. trip delays).

4.3.6 CO₂ Emissions Avoided

By providing frequency response, the fleets of EVs can avoid resorting to Combined Cycle Gas Turbines (CCGTs) standing by to respond to grid contingencies, therefore emitting greenhouse gases. Here, the system savings are computed in terms of carbon emissions due to the frequency response provided by EVs, assuming an emission rate of 368 gCO₂ equivalent/kWh for CCGTs. The results are presented in Table 4.3 for a larger fleet of 5,000 EVs with the same characteristics as the ones used in Section 4.3.

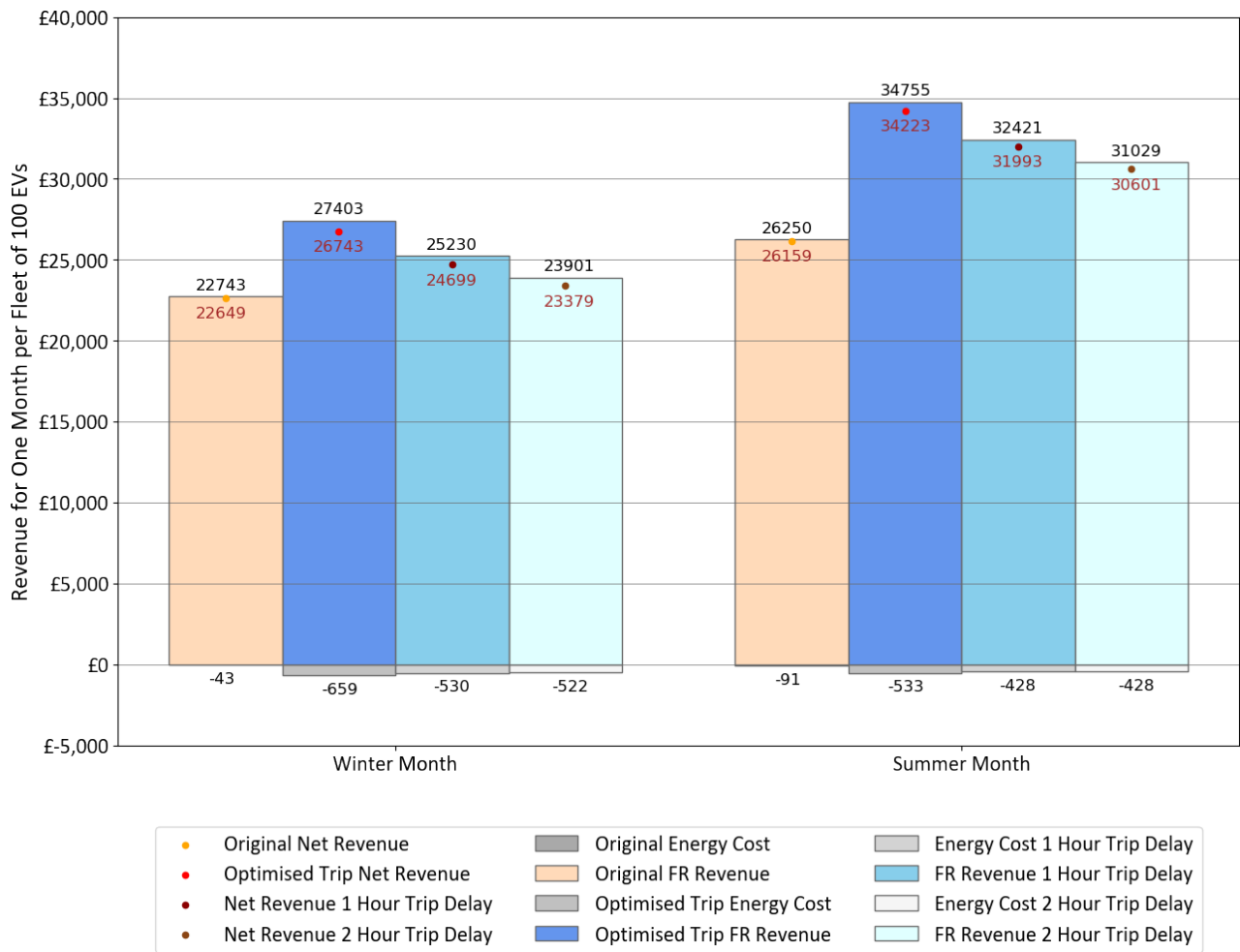


Figure 4.12: Sensitivity Analysis of Maintenance Fleet Revenues Considering Trip Length Delays

Table 4.3: CCGTs and kg of CO₂ Avoided per Month per 5,000 EVs

	Winter		Summer	
	Delivery	Maintenance	Delivery	Maintenance
CCGTs Avoided	1.1	1.15	1	1.05
CO ₂ Avoided (kg)	67,000	71,000	62,500	66,500

The number of CCGTs avoided was calculated using the nadir constraint referred to in Section 4.2.4, solving for x as per equation 4.21. The variables in the nadir constraint are H, PFR and DC. As H and PFR are both provided simultaneously by synchronous generators (e.g. CCGTs), it is possible to input the contribution in DC from the EVs (i.e. DC_{EVs}) and see what the subsequent reduction in provision of H and PFR is from the CCGTs (where x is the number of CCGTs avoided). It is assumed that each CCGT is a 500MW plant with a 5s inertia constant, operating at a minimum stable generation of 250MW. The CCGTs are able to provide 75MW (i.e. 15% of their capacity) for PFR. As the equation is non-linear, the calculation was solved hour by hour and then averaged for the month to produce the results in Table 4.3.

$$\left[\frac{H_{\text{tot}} + x \cdot H_{\text{CCGTs}}}{f_0} - \frac{(DC_{\text{tot}} - DC_{\text{EVs}}) \cdot 1\text{s}}{4 \cdot \Delta f_{\text{max}}} \right] \cdot \frac{PFR_{\text{tot}} + x \cdot PFR_{\text{CCGTs}}}{10\text{s}} = \frac{[P_{\text{infeed}} - (DC_{\text{tot}} - DC_{\text{EVs}})]^2}{4 \cdot \Delta f_{\text{max}}} \quad (4.21)$$

4.4 Conclusion

This chapter described and implemented a new approach to transport and energy sector integration. In order to quantify the value of EV fleet operation in the current and future power system, fleets of EVs were modelled participating in energy and balancing service markets. The operation of these fleets was not just optimised for charging and discharging (as per Chapter 3 of this thesis, upon which this chapter expands), but the optimal trip time was also found, in order to maximise revenues. This approach limited battery degradation and accurately captured balancing service provision both from reducing charging and increasing discharging.

The flexibility of two commercial EV fleets from the E-Flex project was characterised, all of which contributed to the central research question of this thesis related to finding the optimum charging, discharging and travel schedules to maximise revenues for EV fleet operators.

The analysis performed in this chapter has shown the significant potential benefits of EVs providing frequency response services in the current and future GB system scenarios, where flexibility is projected to be more valuable. Real-world data was used to accurately characterise the flexibility of commercial fleets using a methodology for scheduling optimal journey times according to frequency response prices. It was shown that such fleets with flexible journeys participating in these markets would increase their revenues by up to 38% in the summer and 12% in the winter. Fleets of an increased volume of 5,000 EVs with the same characteristics will be able to replace at least one CCGT plant for frequency control purposes, and the equivalent of at least 62,500 kg of CO₂ per month.

In this chapter, investigating the effects of uncertainty (for example in trip length, due to traffic conditions) was limited to the performance of multiple sensitivity analyses. The question this chapter raises is, how does the EV fleet account for uncertainties in the energy price, arrival time of EVs and their travel energy? It is this question that Chapter 5 addresses.

Chapter 5

Real-time Charging Scheduling of Electric Vehicles: Reinforcement Learning

5.1 Introduction

As discussed throughout this thesis, EVs could present an opportunity to provide energy and grid services that generate value both to the system and also to the EV fleet operator (and EV owner). In order to unlock value from EVs, the EV charging scheduling problem has been tackled using model-based approaches in the literature as well as in Chapters 3 and 4 of this thesis. These approaches necessitate that the detailed physical parameters of the problem are well known. Running models at scale can be time-consuming and these models have difficulty handling system dynamics and uncertainties.

Reinforcement learning (RL) has gained traction in this area, being model-free, data driven and applied in real-time. RL algorithms have the advantage of training on existing data, learning the best charging schedules and applying them to unknown (and hence uncertain) scenarios. Papers in this area to date have focused on arbitrage in the energy market. When an ancillary

service has been considered in problems in the literature, charging strategies are produced using algorithms characterized by discrete state and / or action spaces.

In this chapter, a novel, deep reinforcement learning (DRL) method to schedule multiple services for a fleet of EVs with uncertain arrival times, EV energy levels and service prices is presented. Real data from the UK demonstration project, E-Flex, is used, as it has been throughout this thesis. Results show that the proposed DRL method outperforms state-of-the-art Q-Learning and Policy Gradient methods in terms of revenues. Furthermore, the DRL method is able to learn a real-time, automated charging strategy for both energy arbitrage and ancillary services under different market scenarios, achieving 94% of potential theoretical revenues. The way this chapter relates to the larger aims of the thesis is by examining the issue of uncertainty from EV travel patterns and services prices, allowing a practical implementation of coordinating charging of EVs. This, in turn, leads to more effective application of the work presented so far in this thesis in the real world.

5.1.1 Related work

Model-based approaches in the literature to coordinate the charging / discharging of EVs under uncertainty use model predictive control and conventional numerical optimization methods, often seeking to maximize revenue for aggregators or EV owners [51], [11]. At scale, these techniques become difficult to implement due to their high computational intensity and need to maintain an accurate physical model [79]. Various scenarios may be forecast in such approaches, in order to perform the optimization, hence an accurate forecasting model is crucial for an accurate result.

Model-free reinforcement learning (RL) approaches have gained more interest recently given their human-like performance potential in the context of decision-making problems [80] and have begun to be applied to problems related to power systems [79]. This machine learning technique has been used in the literature to facilitate effective control for coordinating EVs, formulating the problem as a Markov decision problem (MDP). RL algorithms do not rely on models and learn in an iterative, data driven way, based on prior experience. RL adapts to

changes in system dynamics and uncertainties, allowing it to be scalable. By training an RL algorithm on travel patterns and pricing data, it learns which choice of charging or discharging actions (i.e. which policy) is most beneficial or profitable. This can then be used to make decisions in real-time, leading to near-optimal results.

A well-known RL algorithm is Q-Learning, the most basic form of which uses a look-up table (Q-Table) to store action-value information for discretized states and actions. The method therefore suffers from the curse of dimensionality, as the computational intensity grows exponentially with an increasing number of actions and states. Too few states and actions, however, will result in sub-optimal solutions. Q-Learning is used to find the charging schedule for EVs, in order to reduce energy costs to EV owners [81]. Q-Learning is also used in [82] to schedule when to charge and discharge EVs arriving at a single charging station with an objective of maximizing revenues from energy for the EV charging station owner.

A whole fleet of EVs are considered by [83], rather than controlling each EV individually, an approach which reduces the state and action spaces of the Q-Learning problem. An important advancement of RL is an effective action-value function (or Q-value function) approximator. The work utilizes the Batch RL algorithm, Fitted Q-Iteration, which uses a set of linear basis functions to estimate the Q-value function. Fitted Q-Iteration is also used in [84] but with a kernel-averaging regression function to find the lowest cost charging solution. The authors in [85] use Fitted Q-Iteration to schedule multiple EVs in order to reduce charging costs. These papers only consider smart charging or grid-to-vehicle (G2V) (i.e. the EVs are not able to discharge), therefore limiting the range of services they are able to provide and hence revenues generated.

The Fitted Q-Iteration RL algorithm can be less scalable and less efficient to train than Deep RL, which uses deep neural networks [80]. Deep RL is first applied to the EV charging strategy problem in [86]. With a forecast electricity price generated with a long short-term memory network (LSTM) and the state of charge of the EV as inputs, a deep Q-network (DQN) algorithm produces a revenue maximizing charging schedule. A DQN was also used to schedule an EV's charging in [87]. While the DQN method allows for continuous state space, the action

space still needs to be discrete. In [88], the authors use a novel Deep Deterministic Policy Gradient (DDPG) technique that they name charging control DDPG (CDDPG). This allows for continuous state and action spaces, enhancing the optimality of the obtained solution. In [89], an approach called Safe RL is applied, which is used to solve the problem constructed as a constrained Markov decision process (CMDP). This is sometimes referred to as 'range anxiety' and is a pay off between customer satisfaction and revenues earned [86]. This eliminates the need for a penalty term, which most other papers apply if the desired state of charge is not reached before the EV departs for the next trip (at the end of the charging session). However, incorporating Lagrange theorem into the RL policy for CMDP requires knowing the physical models to be handled, which counters the very essence of the model-free paradigm.

The vast majority of work in this area, including the papers above, only consider minimizing the energy cost to charge (in the case of G2V) or maximizing the net energy revenue, given by the difference between energy revenue when discharging minus energy cost when charging (in the case of V2G), while ensuring EV user requirements for travel are met. These are summarised in Table 5.1 below, where this service is referred to as energy arbitrage. As discussed, EVs have substantial potential to provide flexibility in the form of balancing services. The work presented in [90] considers EVs' availability to provide balancing services, maximising net revenues for the EV owner. The Q-Learning technique includes a Q-Table with three actions (to charge, discharge or provide availability for balancing services) and stores the reward associated with each of these in a discretized state space from the perspective of a single EV. Here, the actions are limited and the services (e.g. energy or balancing service provision) do not occur simultaneously. In one other work identified that considers EVs providing another service other than energy arbitrage and solved using RL, the objective is to maximize the performance of EVs in responding to balancing service signals [91]. This is done by minimizing the difference between delivered balancing service capacity and the balancing service requirement and is solved using a Q-Table from the perspective of the aggregator of multiple EVs. In [92], balancing services are offered, as well as energy arbitrage, but the action space is limited by the Double DQN approach. Also, only G2V is considered. In this work, we consider multi-service (i.e. simultaneous) energy arbitrage and balancing service provision, with V2G and an RL approach -

Table 5.1: Table of Relevant Works that Use Reinforcement Learning for the EV Scheduling Problem

Reference	Methodology	Market Segment Considered	Charging Mode
[81]	Q-Learning	Energy arbitrage	G2V
[93]	Q-Learning	Energy arbitrage	G2V
[82]	Q-Learning	Energy arbitrage	V2G
[83]	Fitted Q-Iteration (Batch RL)	Energy arbitrage	G2V
[84]	Fitted Q-Iteration (Batch RL)	Energy arbitrage	G2V
[85]	Fitted Q-Iteration (Batch RL)	Energy arbitrage	G2V
[86]	DQN	Energy arbitrage	V2G
[87]	DQN	Energy arbitrage	V2G
[89]	Safe Deep RL	Energy arbitrage	V2G
[88]	CDDPG (Charging DDPG)	Energy arbitrage	V2G
[94]	Continuous SAC	Energy arbitrage	V2G
[91]	Q-Learning	Balancing services	V2G
[90]	Q-Learning	Energy arbitrage and balancing services	V2G
[92]	DDQN (Double DQN)	Energy arbitrage and balancing services	G2V
This work	PPO	Energy arbitrage and balancing services	V2G

proximal policy optimization (PPO) - that allows for continuous action and state spaces.

An RL approach is very much in line with plans from the Energy System Operator in the Great Britain, National Grid, to move procurement of FR closer to real time in response to stakeholder feedback [36]. Doing so would enable the market participation of more distributed energy resources (including aggregators of EVs), who are not able to accurately forecast their availability over longer time horizons. Therefore, the real-time scheduling ability of RL has potential to increase access of flexible resources and reduce overall inefficiencies in the market.

When training the algorithms, the arrival times, departure times and energy used for travel of the EVs in the above works is often assumed to be a normal distribution around typical commuting patterns. For example, commuting fleets leave at approximately 8am and return at approximately 6pm (times which seem to be based on assumptions, not data, such as the approach adopted in Chapter 4). This is limited in that if the algorithm is trained on such data and not on real data, it will only be best at predicting charging schedules with similar driving patterns (although in time it will adapt). Hence, the use of real driving data for fleets in this chapter contributes to the quality of the results.

5.1.2 Motivation and Contributions

This chapter seeks to answer the question, how can fleet operators account for uncertainty in travel patterns and service prices to schedule EV charging and discharging with V2G in real-time using machine learning? Based on the review of existing literature on RL-based EVs' scheduling (Table 5.1), a significant research gap was identified, which drives the motivation of this chapter: no previous work has comprehensively investigated simultaneous and coordinated scheduling of energy and balancing services provision of EVs, while at the same time considering their V2G potential. The papers that lie closest to this objective are [90], which does not allow simultaneous scheduling of energy and balancing services provision and [92], which does not consider V2G. To the best of the author's knowledge, the following contributions are achieved:

- The energy and balancing services provision scheduling problem of an EV with V1G and V2G capability is formulated as a Markov decision process (MDP).
- A novel Deep RL method is developed to address the formulated problem, namely Proximal Policy Optimisation (PPO).
- This chapter uses real-world commercial EV fleet data from the E-Flex demonstration project to train and test the examined learning methodologies.
- Case studies employing this real-world data demonstrate the advantages of the proposed approach over other state-of-the-art methods (Deep Q-Network and Deep Deterministic Policy Gradient).

The remaining part of this chapter is organised as follows: Section 5.2 describes the model based mathematical formulation of the EV charging scheduling problem. In Section 5.3, the problem is formulated as a Markov decision process, including the state and action space description and system dynamics. Following this, state of the art Reinforcement Learning methodologies are discussed in Section 5.4. The inputs and implementation of case studies are outlined in Section 5.5 and detailed results are presented in Section 5.6. Finally, conclusions are discussed in Section 5.7.

5.2 Model Based Formulation of EV Scheduling Problem

As explained in Section 5.1.2 and illustrated in Figure 5.1, we focus on the scheduling problem of EVs with V2G capability that provide both energy and balancing services. This implies that the EV controller has a dual objective: 1) charge power from the grid during periods with low energy prices and discharge power to the grid during periods with high energy prices, and 2) coordinate this energy arbitrage function along with the provision of balancing services, which yields further revenues. Following the approach adopted in [95], we consider two generic types of balancing services: a) upward balancing service, implying increase of EV discharging power / reduction of EV charging power with respect to their baseline level (which is prescribed by their energy transactions), and b) downward balancing service, implying reduction of EV discharging power / increase of EV charging power with respect to their baseline level. Going further, and still following [95], the present modelling approach is limited to trading of the availability of EVs with V2G to increase / reduce their charging / discharging power, and the utilization process of such balancing services is not considered. It should be noted that the two above functions (energy arbitrage and balancing services provision) are naturally related (in contrast to the assumption of paper [90]), since the available amount of balancing services provided by the EVs depends on their energy baseline. For instance, if an EV battery is close to empty, its ability to discharge to provide balancing services is low and hence it would not be able to participate in such a service.

Based on the previous paragraph, the objective function of the considered EV is formulated as (5.1) and lies in the maximization of the net revenues of the EV, given by the energy revenues from discharging energy (first term) minus the energy costs for charging energy (second term) plus the balancing revenues from providing upward (third term) and downward (fourth term) balancing services.

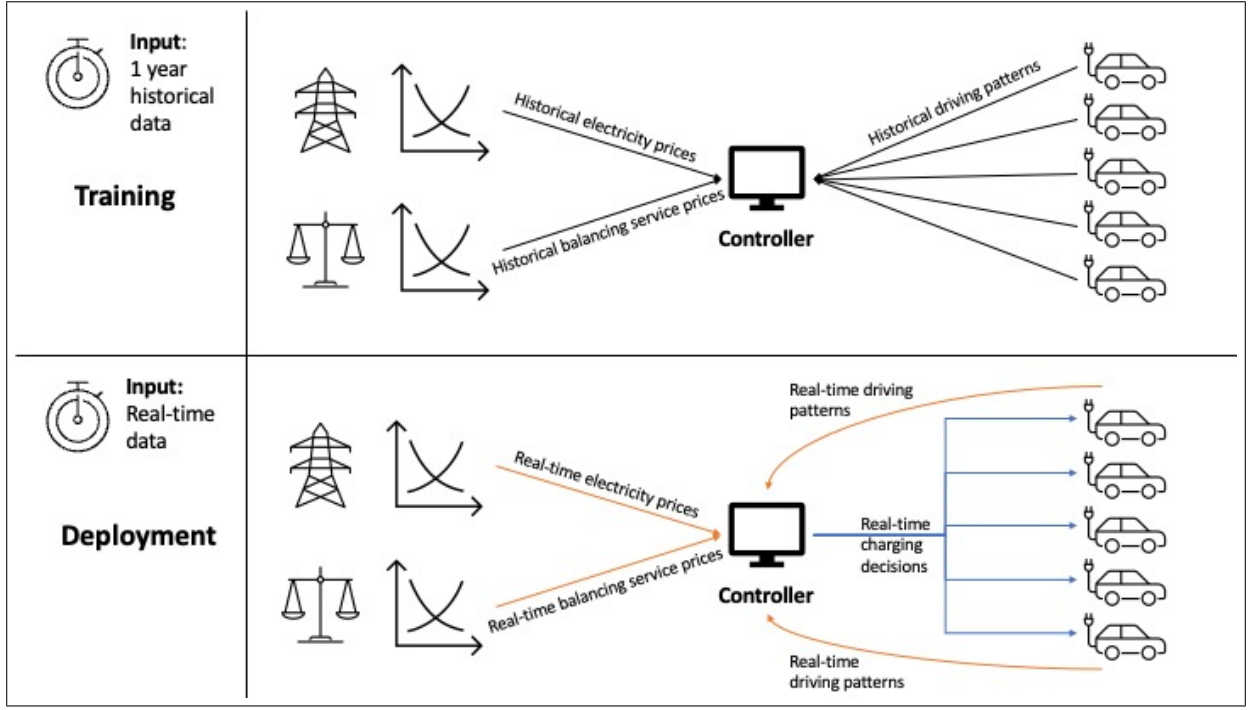


Figure 5.1: Structure of proposed EV smart charging problem

$$\text{maximise} \left(\sum_{t \in T^{gr}} \pi_t (D_t - C_t) + BS_t^{up} \pi_t^{BSup} + BS_t^{dw} \pi_t^{BSdw} \right) \quad (5.1)$$

Going further, this net revenues' maximization problem is subject to the following operating constraints:

$$E_t = E_{t-1} + (C_t \eta_c - \frac{D_t}{\eta_d}) \cdot \Delta t - E_t^{tr}, \forall t \quad (5.2)$$

$$E_{min} \leq E_t \leq E_{max}, \forall t \quad (5.3)$$

$$E_{t_d} = E^{req} \quad (5.4)$$

$$0 \leq C_t \leq P^{c,max} \cdot A_t \quad (5.5)$$

$$0 \leq D_t \leq P^{d,max} \cdot A_t \quad (5.6)$$

$$0 \leq BS_t^{up} \leq (C_t + (P^{d,max} - D_t)) A_t \quad (5.7)$$

$$0 \leq BS_t^{dw} \leq ((P^{c,max} - C_t) + D_t) A_t \quad (5.8)$$

$$BS_t^{up} \leq \frac{(E_{t-1} - E_{min})\eta_d}{\Delta t} \quad (5.9)$$

$$BS_t^{dw} \leq \frac{E_{max} - E_{t-1}}{\eta_c \Delta t} \quad (5.10)$$

Constraint (5.2) expresses the EV battery's energy balance, accounting for the energy needed for traveling purposes as well as charging and discharging losses. Constraint (5.3) represents the limits of the battery's energy level, while constraint (5.4) ensures that the energy level upon departure is equal to a fixed parameter specified by the user and encapsulating its range anxiety. Constraints (5.5)-(5.6) represent the limits of the charging and discharging power when the EV is connected to the grid.

Constraints (5.7)-(5.8) express the power-related limits of balancing services provision. Specifically, constraint (5.7) limits the upward balancing provision of the EV to the sum of its charging reduction margin (out of the parentheses) and its discharging increase margin (in the parentheses), while constraint (5.8) limits the downward balancing provision of the EV to the sum of its charging increase margin (in the parentheses) and discharging reduction margin (out of the parentheses). Going further, constraints (5.9)-(5.10) express the energy-related limits of balancing service provision. Specifically, constraint (5.9) limits the upward balancing provision of the EV to its energy reduction margin (considering that both charging reduction and discharging increase tend to reduce the energy level of the EV battery), while constraint (5.10) limits the downward balancing provision of the EV to its energy increase margin (considering that both charging increase and discharging reduction tend to increase the energy level of the EV battery). Overall, constraints (5.7)-(5.10) clearly indicate that the provision of balancing

services by the EV is coupled with its energy-related actions, in contrast to the approach of the previous relevant paper [90].

5.3 EV Scheduling Problem as a Markov Decision Process

As the aim is to address the EV scheduling problem described in Section 5.2 through a model-free RL approach, the starting point lies in reformulating this problem as a Markov Decision Process (MDP) with discrete time steps. Elements of an MDP include: 1) a state space $\mathcal{S}$, encapsulating the information that the EV agent observes from its environment, 2) an action space $\mathcal{A}$, encapsulating the set of actions that the EV agent can take, 3) a transition dynamics distribution with conditional transition probability $p(s_{t+1}|s_t, a_t)$, satisfying the *Markov property*, i.e. $p(s_{t+1}|s_t, a_t) = p(s_{t+1}|s_1, a_1, \dots, s_t, a_t)$; 4) a reward $r: \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$; and 5) a discount factor $\gamma \in [0, 1]$ that is used to determine the relative importance of future and immediate rewards. The elements of the MDP in the context of the examined EV scheduling problem are detailed in the sections below.

5.3.1 State Space

The environment state is defined as a 6-dimensional vector

$$s_t = [t, A_t, E_t, \pi_t, \pi_t^{BSup}, \pi_t^{BSdw}] \quad (5.11)$$

which consists of the time step t , the availability of the EV (indicating whether the EV is connected to the grid or not) at time step t , the energy level in the EV battery at the end of time step t , and the energy and balancing prices at time step t . It should be noted that the time step of departure and the energy level required upon departure are assumed known ahead of time, while the time step of arrival and the energy level upon arrival are uncertain; the latter also applies to the energy and balancing prices.

5.3.2 Action Space

The action of the EV agent at time step t is denoted as $a_t \in [-1, 1]$, representing the magnitude of discharging (negative) or charging (positive) power as a percentage of the maximum discharging or charging power of the charger, respectively.

5.3.3 System Dynamics

The system dynamics describe how actions are mapped to states. Of the state elements, t , A_t , π_t , π_t^{BSup} and π_t^{BSdw} are all inputs from data, whereas E_t is calculated and then used by the MDP in the next state. In other words, the resultant energy level of the EVs is calculated by the state transition, given the time to departure and prices of energy and balancing services up and down. The equations used to determine the energy level for the next state are described here.

The actual charging / discharging power of EV in (5.12) below is imposed ex-post by the environment according to the power limits (corresponding to constraints (5.5) and (5.6)) on the left hand side of the min operator and the energy limits (corresponding to constraint (5.3)) on the right hand side of the min operator.

$$\begin{cases} C_t = \min \left(a_t \cdot A_t \cdot P^{c,max}, \frac{(E_{max} - E_{t-1})}{\eta_c \cdot \Delta t} \right) & \text{if } a_t \geq 0 \\ D_t = \min \left(a_t \cdot A_t \cdot P^{d,max}, \frac{(E_{t-1} - E_{min})\eta_d}{\Delta t} \right) & \text{if } a_t \leq 0 \end{cases} \quad (5.12)$$

The feasible upward and downward balancing service availability in each time step is also calculated from the action chosen, based on available energy in the battery and maximum power. This is important, should the balancing service be called on. Equations (5.13) and (5.14) below relate to the balancing service constraints (5.7) - (5.10).

$$BS_t^{up} = \min \left((C_t + (P^{d,max} - D_t)) \cdot A_t, \frac{(E_{t-1} - E_{min})\eta_d}{\Delta t} \right) \quad (5.13)$$

$$BS_t^{dw} = \min \left(((P^{c,max} - C_t) + D_t) \cdot A_t, \frac{E_{max} - E_{t-1}}{\eta_c \cdot \Delta t} \right) \quad (5.14)$$

Finally, the energy level at the end of the current time step, E_t , is calculated for use in the next state, as per constraint (5.2) of the model based formulation.

$$E_t = E_{t-1} + (C_t \eta_c - \frac{D_t}{\eta_d}) \cdot \Delta t - E_t^{tr} \quad (5.15)$$

It is worth noting that the balancing service availability does not directly affect the next energy level. This is because it is an availability and the utilization is not considered here. However, the balancing service availability that is offered is feasible were this service to be called on, according to equations (5.13) and (5.14).

5.3.4 Reward

The reward is calculated by multiplying the charging or discharging level (i.e. feasible action) by the price for energy and adding the balancing service availability that is also offered multiplied by the balancing service price. In order to meet the requirement to be charged at the start of the next journey, a penalty is applied in the predefined safety period t_s prior to departure. If the state of charge of the battery is far from the required energy level within this safety period (i.e. before departure) then a penalty applies. Using this technique results in the battery being charged to the required state, in order to avoid a lower reward in these last two time steps. To this end, the final reward function for EV agent is designed based on the below two conditions:

$$r(s_t, a_t) = \begin{cases} \pi_t(D_t - C_t) + \pi_t^{BSup} BS_t^{up} + \pi_t^{BSdw} BS_t^{dw} - \mu \cdot \max(0, E_{req} - E_t)^2 & \text{if } t > t_d - t_s \\ \pi_t(D_t - C_t) + \pi_t^{BSup} BS_t^{up} + \pi_t^{BSdw} BS_t^{dw} & \text{otherwise} \end{cases} \quad (5.16)$$

In the first condition, the penalty term is added. Otherwise in the second condition, the EV

agent only cares about the business case when plugged into the grid.

5.3.5 Objective

The above MDP process continues for each time step until the episode (i.e., overnight charging session) ends, the EV agent then computes a trajectory of states, actions, and rewards: $\tau = s_1, a_1, r_1, s_2, \dots, r_T$ over $\mathcal{S} \times \mathcal{A} \times \mathcal{R} \rightarrow \mathbb{R}$. The objective is finding an optimal policy $\pi(a|s)$ that maximizes its cumulative discounted reward

$$R_i = \sum_{t=0}^T \gamma^t r(s_t, a_t), \quad (5.17)$$

where $\gamma \in [0, 1)$ is the discount factor determining the relative importance of future and immediate rewards, and T is the time horizon.

5.4 Methodology: Reinforcement Learning

In order to solve the above MDP formulated in Section 5.3, we would like to apply various RL/DRL methods in this chapter. In general, there are two categories. The first category is value-based RL method, where the EV agent learns the state or state-action value and acts according to the highest value in that particular state. Q-learning and Deep Q-Network (DQN) are two popular value-based RL methods that have been applied to many EV scheduling problems in the literature. The second category is policy-based RL method, where the EV agent learns the best stochastic or deterministic policy function by directly sampling policies [96]. Deep deterministic policy gradient (DDPG) and Proximal Policy Optimisation (PPO) two popular policy-based RL methods that have been applied to many EV scheduling problems in the literature. The fundamental difference between two categories is that policy-based RL methods can deal with the continuous action space while the value-based RL methods cannot. This is very important because the studied EV scheduling problem in this chapter is characterized by continuous domain. The detailed introductions of various RL methods have been

presented below.

5.4.1 Q-learning and Deep-Q Network (DQN)

Q-Learning [97] is a tabular approach based on temporal difference (TD) learning [98]. It is assumed that both state and action are in discrete spaces (e.g., $\mathcal{S}$ has limited possible states and $\mathcal{A}$ has limited potential actions), the optimal Q-value function $Q^*(s, a)$ can be represented as a table. In observing the current state s_t , the optimal action can be selected as:

$$a_t = \underset{a \in \mathcal{A}}{\operatorname{argmax}} Q^*(s_t, a) \quad (5.18)$$

that means finding the maximum Q-value of the row corresponding to state s_t , and returning the action associated with that Q-value. In Q-learning, a Q-table is used to approximate the Q-value function $Q^*(s, a)$. It first initializes all elements in the table to zero and then updates one element of the table at a time. Eventually, the Q-table will converge to the optimal $Q^*(s, a)$. In order to update this Q-table, it uses the optimal Bellman equation [96] and can write the updated Q-table as:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \underbrace{\left[r_t + \gamma \overbrace{\max_{a_{t+1}} Q(s_{t+1}, a_{t+1})}^{\text{target Q}} - Q(s_t, a_t) \right]}_{\text{TD error}}, \quad (5.19)$$

where α is the learning rate that governs the Q-table's updating steps. It is important to note that when using a tabular approach, the Q-value function can be represented as a large two-dimensional table. That is, there is a separate entry for each discrete state and action. However, this approach will be very inefficient when solving the task with a large data space, suffering severely from the curse of dimensionality [80]. It is this very limitation that has made this particular methodology infeasible to apply to the problem this work examines.

In order to overcome the discrete state space in Q-learning, DQN [80] employs a deep neural network (DNN) (parameterized by θ) as a function approximator to represent the Q-value function in multi-dimensional continuous state space $Q(s_t, a_t) \approx Q_\theta(s_t, a_t)$. Specifically, DQN

learns this Q-value function $Q_\theta(s_t, a_t)$ corresponding to the optimal policy by minimizing the loss (i.e., TD error):

$$\mathcal{L}(\theta) = \mathbb{E}_{s_t, a_t, r_t, s_{t+1} \sim \mathcal{R}} [(r_t + \gamma \max_{a_{t+1}} Q_{\theta'}(s_{t+1}, a_{t+1}) - Q_\theta(s_t, a_t))^2], \quad (5.20)$$

where $Q_{\theta'}(\cdot)$ is a target Q-value function whose parameters are periodically updated with the most recent $Q_\theta(\cdot)$, which can help stabilize the training performance. Another crucial technique for stabilization in DQN is the use of an experience replay buffer $\mathcal{R}$, which contains tuples (experiences) (s_t, a_t, r_t, s_{t+1}) that the agent interacts with the environment. It is known that there is a correlation between two consecutive experiences because the state transition is continuous. If directly taking a batch of experiences in sequence as the training set, the policy is easy to overfit, since the training samples are not independent [99]. To solve this problem, we can randomly select a small number of experiences from the buffer $\mathcal{R}$ as a batch, which not only ensures that the training samples are independent and equally distributed, but also makes the size of each batch small enough to accelerate the training speed [80].

5.4.2 Deep Deterministic Policy Gradient (DDPG)

DDPG is a successful DRL method to deal with high-dimensional and continuous state and action spaces that features an actor-critic architecture and employs two DNNs with different purposes [100], aiming to derive directly the deterministic policies $\mu_\phi : \mathcal{S} \rightarrow \mathcal{A}$. The actor network μ_ϕ takes as input a state s and implements the policy improvement task, updating the policy with respect to the estimated Q-value function and outputting a continuous action $a = \mu_\phi(s)$. The critic network Q_θ takes as input a state s and an action a and outputs a scalar estimate of the Q-value function $Q_\theta(s, a)$.

Similarly to DQN, DDPG also incorporates an experience replay buffer $\mathcal{R}$ that stores the past experiences (s_t, a_t, r_t, s_{t+1}) and samples a minibatch of experiences to update the networks. Furthermore, DDPG introduces target networks for both actor and critic, denoted as $\mu_{\phi'}(s_t)$ and $Q_{\theta'}(s_t, a_t)$, respectively, then adopts soft update that lies in restricting the target values to

change slowly so as to stabilize the learning process, which can be expressed as $\phi' \leftarrow \nu\phi + (1 - \nu)\phi'$ and $\theta' \leftarrow \nu\theta + (1 - \nu)\theta'$ with the updating rate $\nu \ll 1$. By employing these two techniques of experience replay buffer and target networks, the parameters θ of the critic network can be optimized to minimize the TD error defined as:

$$\mathcal{L}(\theta) = \mathbb{E}_{s_t \sim \rho^\mu, a_t \sim \pi_\phi} [(Q_\theta(s_t, a_t) - y_t)^2], \quad (5.21)$$

where the target value is:

$$y_t = r_t + \gamma Q_{\theta'}(s_{t+1}, \mu_{\phi'}(s_{t+1})). \quad (5.22)$$

According to the deterministic policy gradient theorem [100], the parameters ϕ of the actor network can be optimized using the gradient ascent algorithm with the computed gradient defined as:

$$\nabla_\phi J(\mu_\phi) = \mathbb{E}_{s_t \sim \rho} [\nabla_\phi \mu_\phi(s_t) \nabla_{a_t} Q_\theta(s_t, \mu_\phi(s_t))]. \quad (5.23)$$

In addition, to aid the agent in thoroughly exploring the environment, we construct an exploration policy $\hat{\mu}(s_t) = \mu_\phi(s_t) + \mathcal{N}(0, \sigma_t^2 I)$ by adding a Gaussian noise $\mathcal{N}(0, \sigma_t^2 I)$ to the actor's output $\mu_\phi(s_t)$.

5.4.3 Proximal Policy Optimisation (PPO)

PPO is an advanced policy gradient (PG) algorithm that can achieve a balance between the ease of implementation, sampling efficiency, and ease of tuning [101]. In other words, training a relatively good performance in the vanilla PG algorithm is very challenging, as it is very sensitive to the learning rate, i.e., a small learning rate takes a long time to make the training converge, while a large learning rate easily falls into the local optimum. However, PPO can effectively address the difficulty by constructing a probability ratio between the new and old policies, and then clipping it within a stable interval. In this case, the PPO policy can be updated in a trust region. Similar to many PG algorithms, PPO is applicable for modelling multi-dimensional continuous state and action spaces.

To model the action characteristics in continuous domain, we generate a set of Gaussian distributions for the policy network parameterized by ϕ to output the corresponding mean and standard deviation for all action dimensions, the stochastic policy $\pi_\phi(a|s)$ is then sampled for the optimal action a_t in state s_t . This stochastic policy can be updated by maximizing its clipped surrogate objective that considers the restriction of policy update:

$$\mathcal{L}_t^{\text{CLIP}}(\phi) = \mathbb{E}_t[\min(\zeta_t \hat{A}_t, \text{clip}(\zeta_t, 1 - \epsilon, 1 + \epsilon) \hat{A}_t)], \quad (5.24)$$

where the first term $\zeta_t \hat{A}_t$ within the operator $\min\{\cdot\}$ indicates the normal policy gradient, while the second term $\text{clip}(\zeta_t, 1 - \epsilon, 1 + \epsilon) \hat{A}_t$ within the operator $\min\{\cdot\}$ trims the policy gradient by clipping the probability ratio ζ_t^d between $[1 - \epsilon, 1 + \epsilon]$. The hyperparameter $\epsilon \in [0, 1]$ is used to truncate the gradient update of the new policy from the old version. In other words, the advantage function $\hat{A}_t$ will be clipped if the probability ratio goes beyond the range $[1 - \epsilon, 1 + \epsilon]$. In PPO policy, the probability ratio ζ_t can be expressed as:

$$\zeta_t = \frac{\pi_\phi(a_t|s_t)}{\pi_{\phi_{\text{old}}}(a_t|s_t)}, \quad (5.25)$$

In addition, the generalized advantage function $\hat{A}_t$ in (5.24) can be expressed as:

$$\hat{A}_t = \delta_t + \gamma \delta_{t+1} + \dots + \gamma^{T-t+1} \delta_{T-1}, \quad (5.26)$$

$$\text{where } \delta_t = r_t + \gamma V_\psi(s_{t+1}) - V_\psi(s_t), \quad (5.27)$$

here $V_\psi(s)$ is the state-value function that can be approximated by a state-value network parameterized by ψ .

5.5 Case Studies: Input Data and Implementation

In this section, case studies are presented to demonstrate the performance and effectiveness of the described PPO method. Several examined scenarios are selected, based on a range of

Table 5.2: Summary of Case Studies

Markets Considered	Charging Mode	Scenario
Baseline / None	Dumb Charging	1
Energy	V1G	2a
	V2G	2b
Energy and Balancing Services	V1G	3a
	V2G	3b

charging modes and electricity markets, reflecting common arrangements found in the literature. The input data is described, followed by the implementation of the selected PPO algorithm. This algorithm is then compared to other state-of-the-art methods in Section 5.6, to show its relative performance.

5.5.1 Case Study Description

The case studies with different charging modes and electricity markets are summarised in Table 5.2. The first is the dumb charging mode, which is the most simplistic and assumes EVs return to depot and immediately charge up to the required level for the next day. The energy market scenarios only consider energy prices, the V1G or smart charging will reduce charging costs by charging at the cheapest times. With the V2G charging mode, the EVs are able to perform energy arbitrage by discharging the energy when it is more expensive, then charging up again when the prices drop. Finally, in the multi-service energy and balancing service market scenarios, both the energy and the balancing service prices are considered. Here, in V1G mode, the EVs are only able to bid availability for balancing services when they are able to reduce their charging. Introducing V2G for this scenario unlocks the potential for EVs not only to perform energy arbitrage but also to provide much greater levels of balancing service availability. By combining the two, the scenario becomes profitable.

5.5.2 Input Data

The time horizon, or episode length, is calculated from the time the EV plugs in until 7am, designed as an overnight charge at depot. The time-steps are in half hourly increments. The

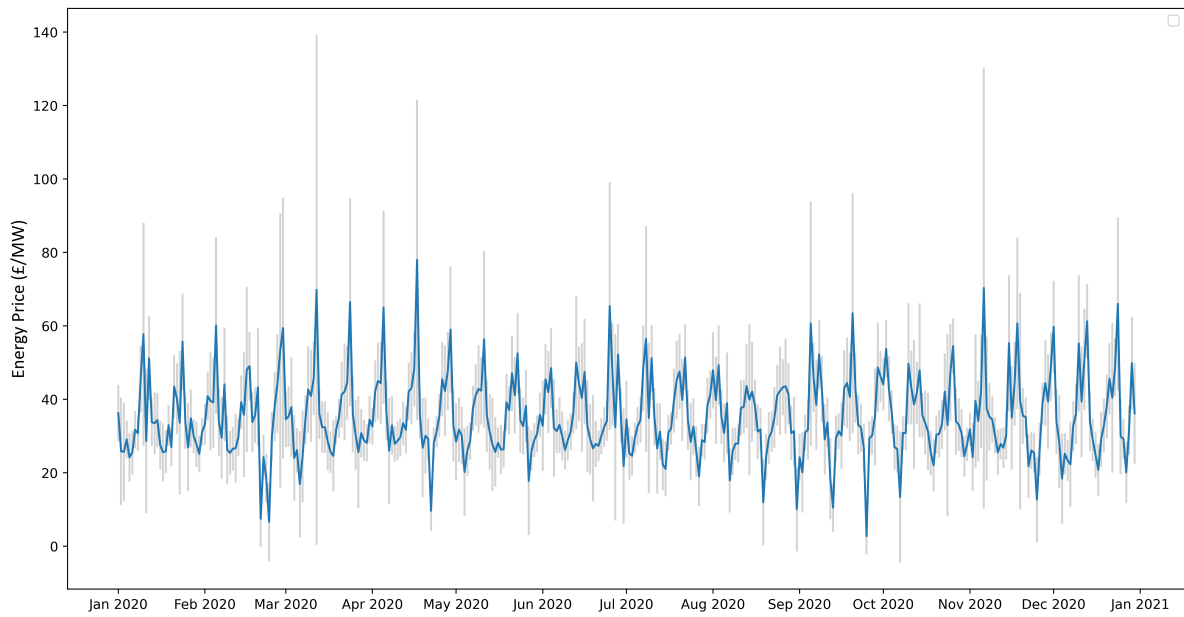


Figure 5.2: Historical Mean and Standard Deviation Daily Electricity Prices for Input Year

travel data used was that of a commercial maintenance fleet from Innovate UK funded V2G demonstration project 'E-Flex', as per Chapters 3 and 4. The fleet of five EVs over 12 months was considered (the year 2020), in order to capture full season variability. Each EV has a battery capacity of 40 kWh and each charger has a rated power of 10 kW (i.e. G2V chargers can charge up to 10 kW and V2G chargers can charge up to 10 kW and discharge up to 10 kW). A time-of-use (TOU) tariff was used, which was based on the wholesale energy prices, both for buying and selling energy. The daily mean and standard deviation of these prices are plotted for one year in Figure 5.2. For balancing services, the 2020 Low Frequency Static product prices from National Grid were used [102]. The daily mean and standard deviation of these prices for the one year of data used is shown in Figure 5.3. The Electricity Forward Agreement (EFA) blocks were not used for the FR availability and it was assumed that bids could be made on a half-hourly basis, close to real time, in the half-hour ahead horizon. This is to demonstrate the ability of the algorithm to make decisions closer to real time. It is also in line with the trend of FR markets being closer to real time in the future.

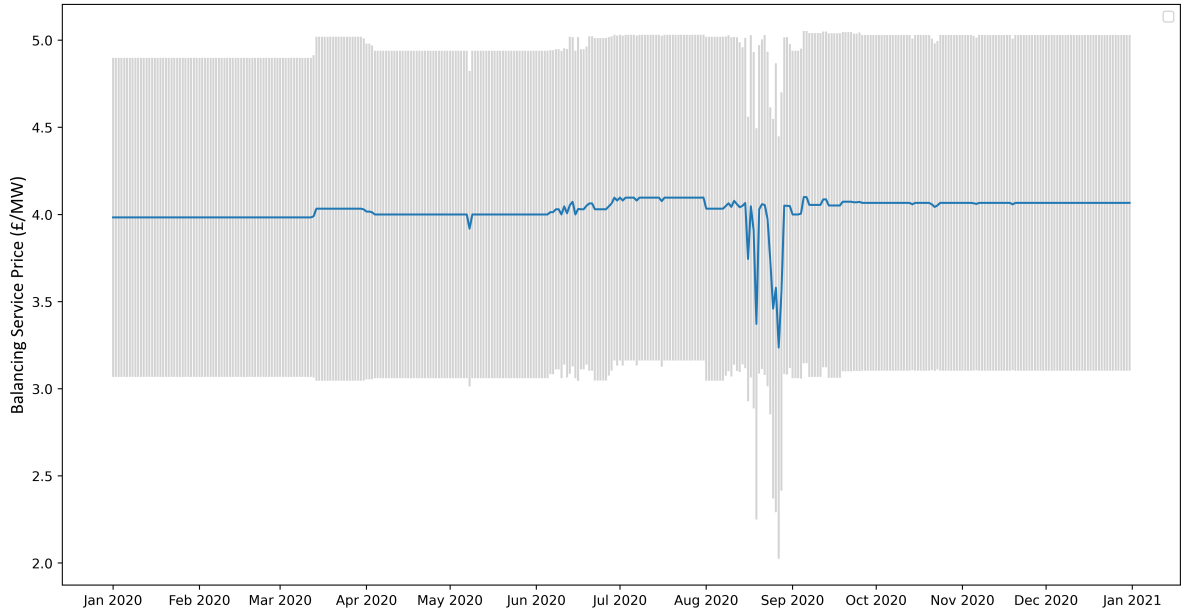


Figure 5.3: Historical Mean and Standard Deviation Daily Balancing Service Prices for Input Year

5.5.3 Implementation

A year of data was used to produce a full set of case studies. This data was split into a training data set of six days a week for a year (312 days), with one randomly selected day a week (52 days total) used as a testing data set. This ensured the testing data set contained a full range of seasonal variability and type of day of the week, as used in [95]. The single agent trained on the data from all five EVs, because they are of the same fleet and have the same usage (are used interchangeably by the drivers). Figure 5.4 shows how the rewards increase as the agent explored the states to discover policies that result in the highest rewards. Once this agent is well trained, an 'unseen' test data set is used.

Once trained, the RL agent produced five charging schedules separately (i.e. one for each EV), with their associated revenue amount. These were then summed here for comparison between methods and between the theoretical benchmark solution. It should be noted the time it took to the RL agent to produce these schedules with the PPO algorithm are approximately 0.01 seconds per EV per day. Hence, it is reasonable to use a single agent for a fleet. In order to meet the requirement for a full charge by the end of the overnight charging session, a penalty term was applied to the last two half-hourly time steps (i.e. the safety period chosen was 2).

5.6 Case Studies: Results and Discussion

This Section details the results of the case studies outlined in Section 5.5. First, the different RL methodologies are applied to Scenario 3b and compared in Section 5.6.1. The proposed PPO method was then applied to all scenarios and compared to the theoretical benchmark solution in Section 5.6.2, and the performance of the approach is demonstrated.

All RL methods in this section have been implemented using Tensorflow 1.15 in Python. The MILP problem was implemented using the Gurobi Optimizer Python environment, with a MIP gap of 0.1%. The case studies have been carried out on a computer with a 3.6 GHz Intel Core i7-7820X 8-Core processor and 64 GB of RAM.

It should be noted that other benchmark methods were considered, including scenario-based stochastic optimisation. However, it was deemed that the results would not be comparable. This is because many scenarios would need to be generated, based on sampling a normal distribution of the arrival time and energy consumed per EV. These many scenarios would be computationally intensive to run and a scenario reduction technique would need to be used. The resultant data set and scenarios would not be comparable to the real world data set that this RL model is trained and tested on. The benefit of the theoretical benchmark chosen (i.e. MILP) is that the same data was used, so as to accurately benchmark the RL results.

5.6.1 Comparison of RL Methods

In this section, two other state-of-the-art methods, DQN and DDPG, are used to compare the PPO result for Scenario 3b (Energy Arbitrage with Balancing Services with V2G). The training process used 312 days of travel data from the fleet of five EVs and price data (as described in Section 5.5). The different learning curves for each of the RL approaches are illustrated in Figure 5.4 and the mean and standard deviation at different episodes for the RL methods are given in Table 5.3.

The implementation of the DRL methods is as follows:

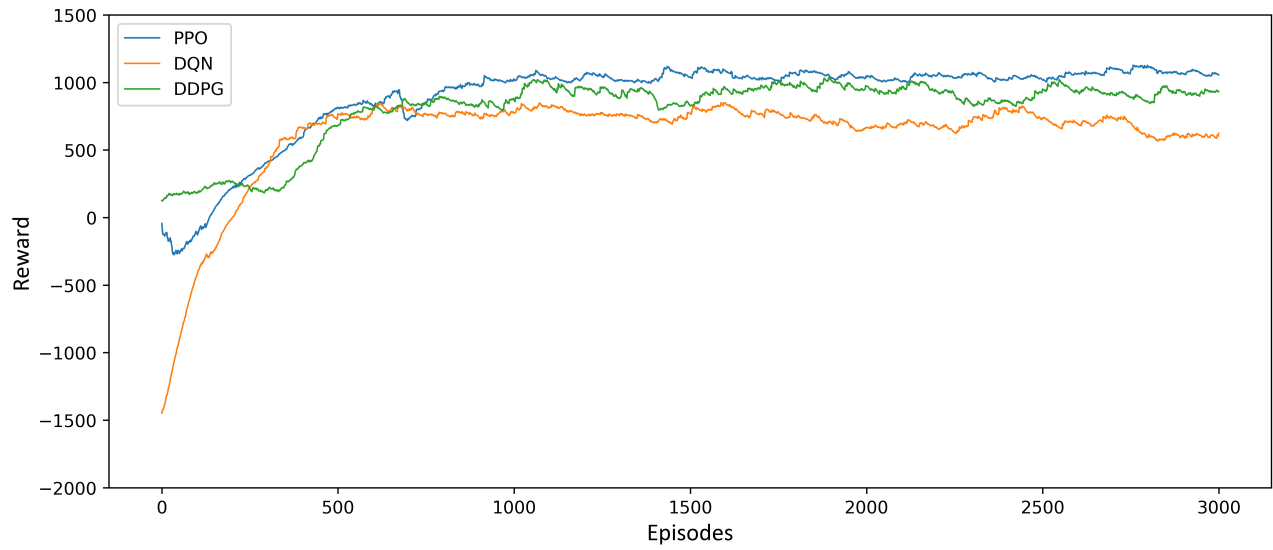


Figure 5.4: Scenario 3b Learning Curve Comparison for All RL Methods

Table 5.3: Mean and Standard Deviation at Different Episodes for Examined RL Methods

		Episode				
		1	100	500	1000	3000
DQN	μ (£)	-1.45	0.09	51	0.64	0.69
	σ (£)	0	0.51	0.67	0.62	0.58
DDPG	μ (£)	0.13	0.23	0.4	0.63	0.83
	σ (£)	0	0.4	0.52	0.59	0.66
PPO	μ (£)	-0.04	-0.26	0.45	0.7	0.94
	σ (£)	0	1.08	0.73	0.74	0.6

Table 5.4: Computational Performance of Different RL Methods

Method	Average CPU time per episode (ms)	Number of episodes	Total CPU time (min)	Average CPU time per EV at execution (ms)
DQN	1108.94	3000	55.45	11.91
DDPG	994.11	3000	49.71	9.93
PPO	65.85	3000	3.29	9.46

Table 5.5: Performance Comparison of Different RL Methods

	Fleet Revenue for Test Period of 52 Days (£)	Accuracy
Benchmark	294.63	
PPO	277.28	94.1%
DQN	210.06	70.0%
DDPG	236.05	80.1%

- DQN: This method employs a Deep Neural Network (DNN), with 19 neurons in the output layer. This half-hour-by-half-hour learning procedure cannot meaningfully exploit information associated with future hours in the state vector. The state vector only includes information associated with the current time step and the previous time step. Specifically, it includes the half-hour identified, the energy level of the EV, the energy price and the balancing service price, resulting in seven neurons in the input layer of the DNN.
- DDPG: Two DNNs are employed for this method, i.e., the online and the target network, for both actor and critic. The Adam optimizer is employed for learning the neural network weights with a learning rate 0.001 and 0.01 for the actor and critic, respectively. For the critic, a discount factor (gamma) of 0.95 is used. Both the actor and critic employ the rectified linearity units (ReLU) for all hidden layers. This method was trained with a mini batch size of 1024.
- PPO: Two DNNs are employed for this method, i.e., the online and the target network, for both actor and critic. The Adam optimizer is employed for learning the neural network weights with a learning rate 0.0001 and 0.001 for the actor and critic, respectively. For the critic, a discount factor (gamma) of 0.99 is used.

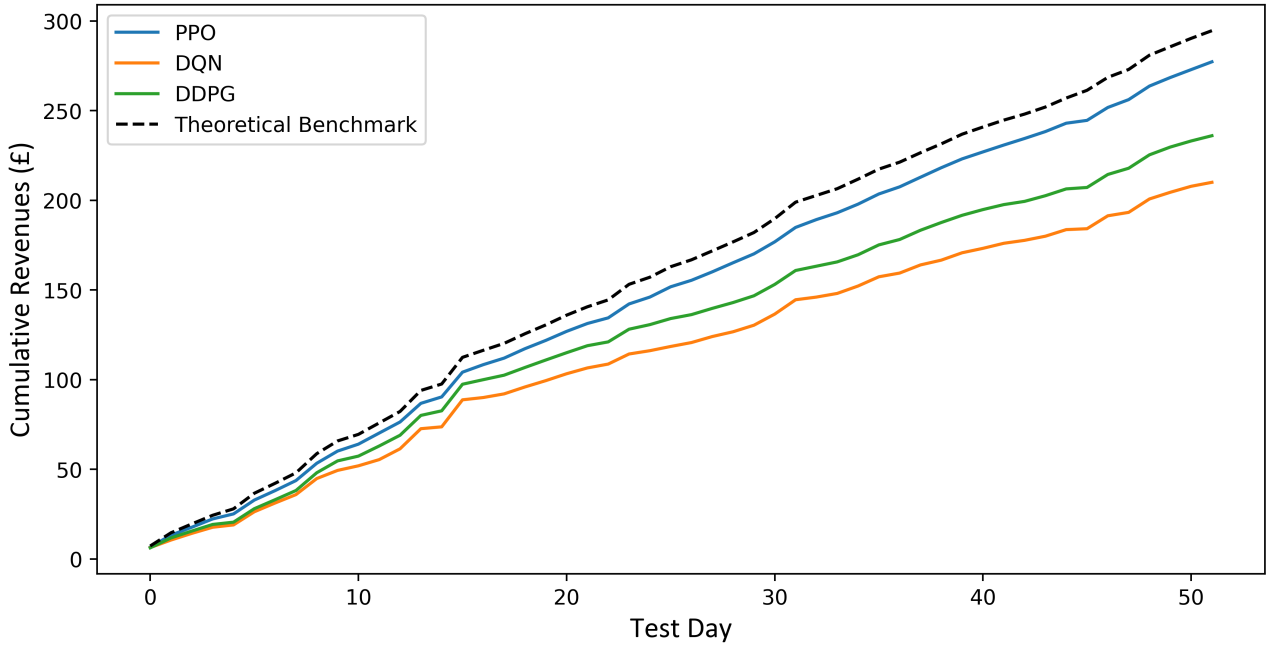


Figure 5.5: Scenario 3b Cumulative Revenue of Test Data Set for All RL Methods

The cumulative fleet revenues for the 52 test days using all three methods is illustrated in Figure 5.5. The end result reflects the accuracy percentages reported in Table 5.5. In order to compare the computational performance, average and overall CPU time for each method, along with average CPU time per EV at execution, are given in Table 5.4. The PPO method is significantly faster than the other methods during training.

Figure 5.6 shows how effective the RL agent is at producing a revenue-maximising schedule for an example test day using the PPO approach. As seen in this schedule, the EV discharges when the energy price is high and charges when it is low. The upward Frequency Response price is higher in the period after 12:00, and a higher volume of FR Up availability is shown to be offered during this period. The theoretical benchmark schedule for the example day in Figure 5.9, shows a similar schedule but with higher peak charging and discharging levels. This is due to the fact that policies and actions within them are sampled randomly in the RL approach, the maximum level of charging for one particular time step is less likely to occur unless its reward is distinctly higher. Example schedules for the DQN and DDPG approaches are shown in Figures 5.7 and 5.8, respectively, for comparison.

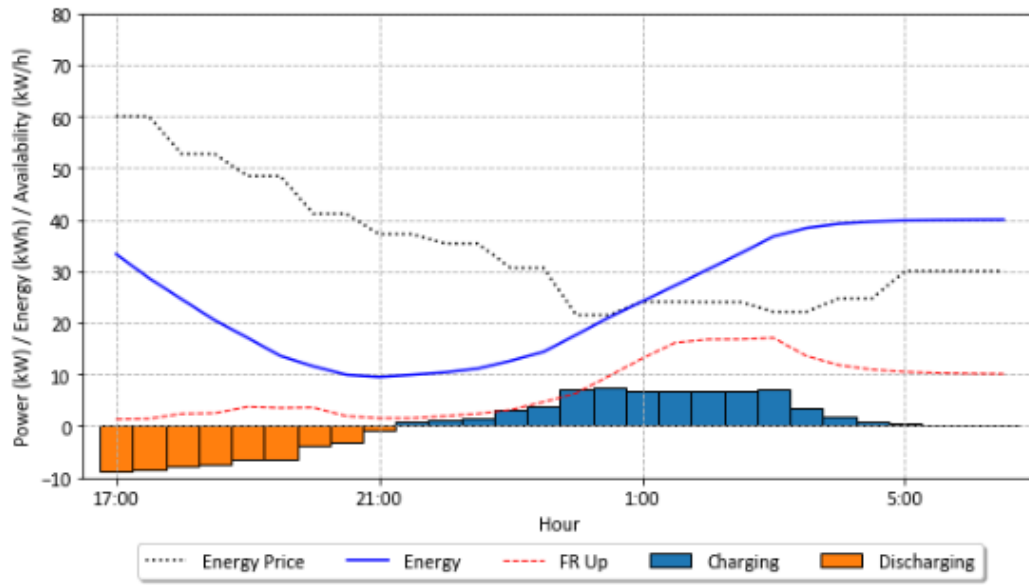


Figure 5.6: Scenario 3b Example Schedule: Produced with PPO Method

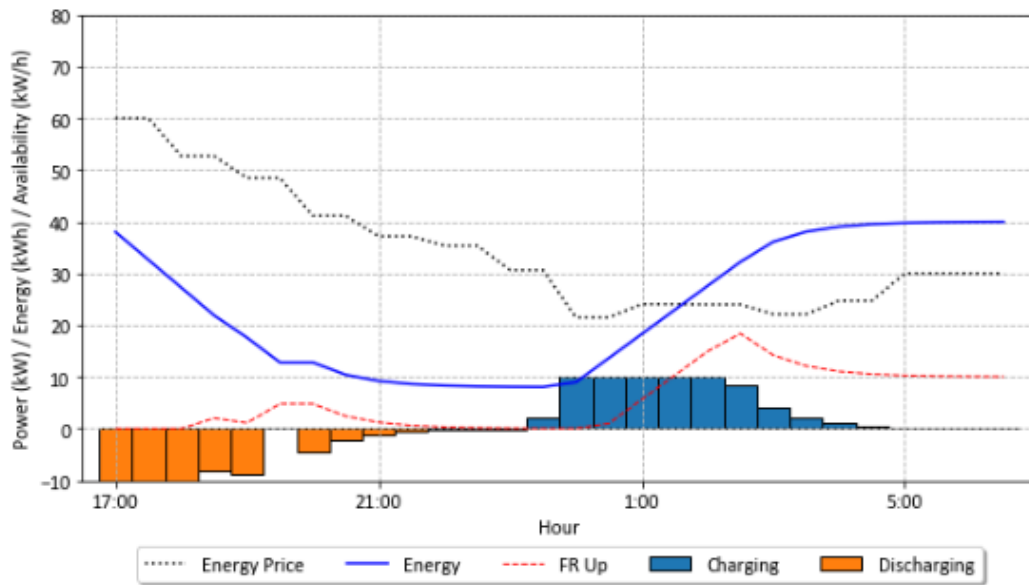


Figure 5.7: Scenario 3b Example Schedule: Produced with DQN Method

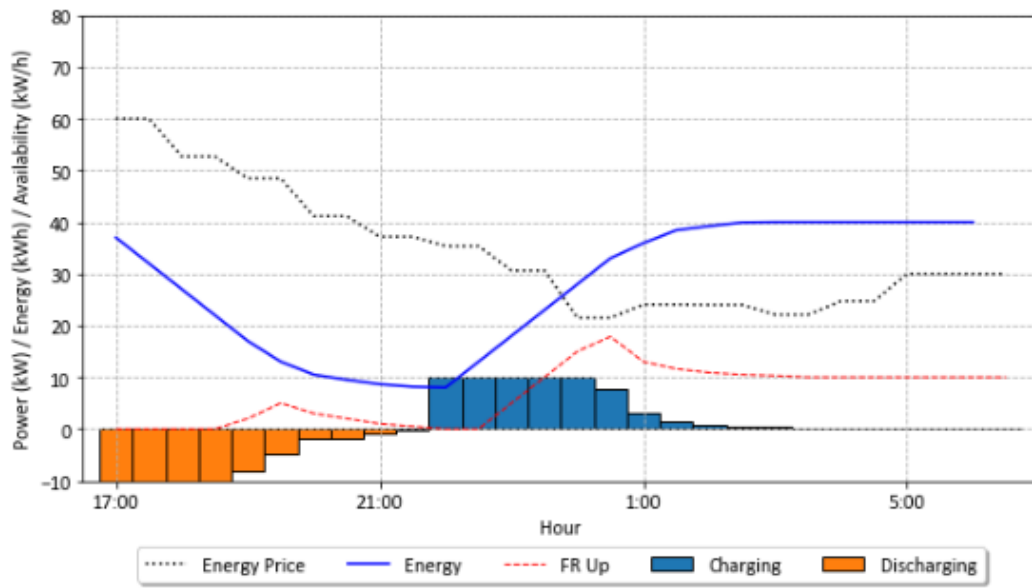


Figure 5.8: Scenario 3b Example Schedule: Produced with DDPG Method

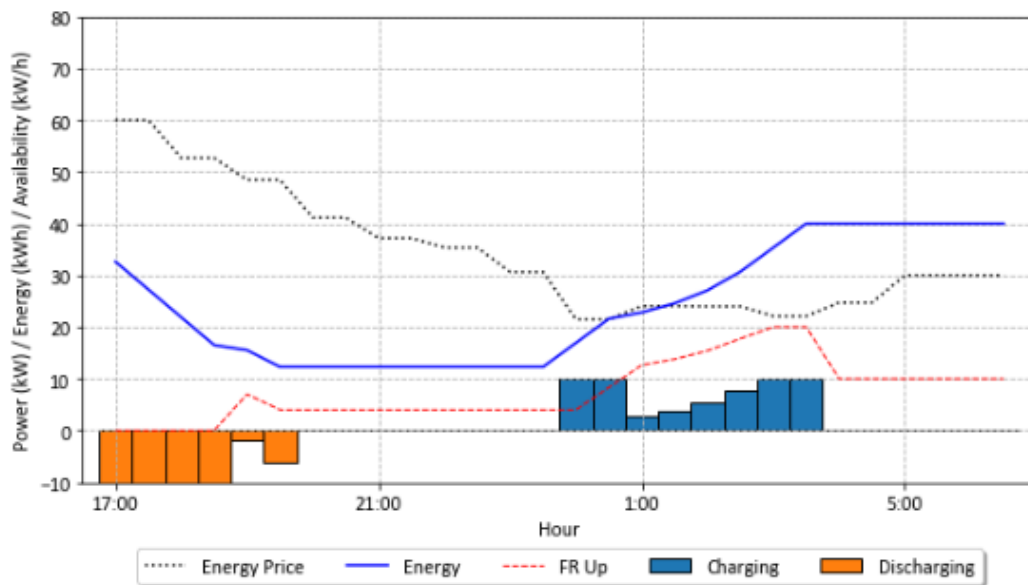


Figure 5.9: Scenario 3b Example Schedule: Theoretical Benchmark Result

Table 5.6: Fleet Revenue for PPO Method Compared to Theoretical Benchmark for All Scenarios

	Revenue for EV Fleet of 5, test period of 52 days (£/fleet)		% Accuracy of PPO
	PPO	Benchmark	
1	N/A	-17.98	N/A
2a	-16.77	-17.09	98.13%
2b	137.47	158.68	86.63%
3a	-14.86	-12.25	78.69%
3b	277.28	294.63	94.11%

5.6.2 All Scenarios Results with PPO Method

The case study results are presented here for the proposed PPO method. The results are compared to the theoretical benchmark solution, obtained using Mixed Integer Linear Programming (the formulation of which is outlined in Section 5.2). The revenue obtained by the fleet over the 52-day test data set for each scenario can be found in Table 5.6.

Example charging and discharging schedules produced by the PPO approach for each of the scenarios as compared to the theoretical benchmark solution are shown below. Scenario 2a, G2V charging mode with energy market participation only, is compared in Figure 5.10 and Figure 5.11. As observed, the PPO charging schedule spreads the charging over the period of low energy prices, as compared to the the theoretical benchmark, which charges in fewer time periods but at a higher power. This accounts for the difference in cost between the two example schedules, where the PPO produced a schedule that cost 95% of the theoretical benchmark.

In Scenario 2b, however, charging and discharging is done to a higher power by the PPO algorithm, but at a slightly earlier time than the theoretical benchmark. This is illustrated in the difference between Figure 5.12 and Figure 5.13. This is most likely due to the penalty applied in the final two time-steps of the charging session in the RL approach, if the EV is not charged to the desired level. For this reason the PPO charged earlier, and produced a schedule, here, that resulted in 87% of the theoretical benchmark revenues.

Figure 5.14 shows the PPO produced example charging schedule for Scenario 3a, compared to the theoretical benchmark schedule in Figure 5.15. Here, again, similar to in Scenario 2a, the charging is spread out over the lowest energy cost periods for the PPO produced schedule.

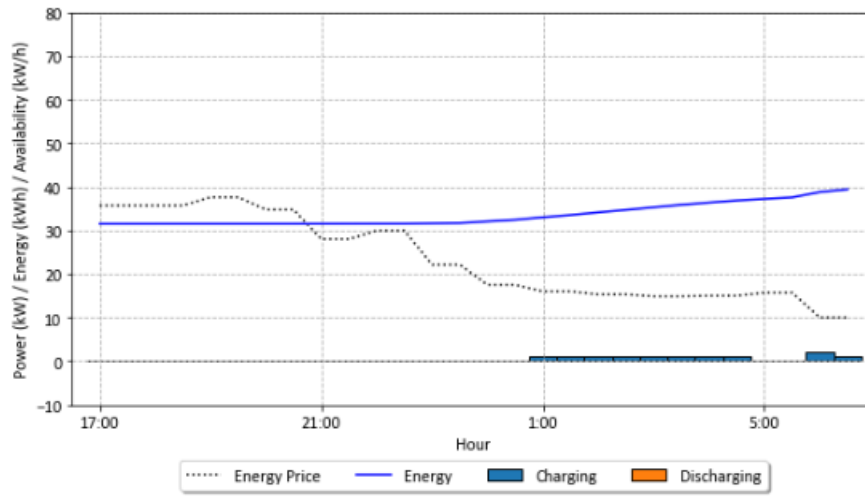


Figure 5.10: Scenario 2a Example Schedule: Energy Arbitrage with V1G produced with PPO Method

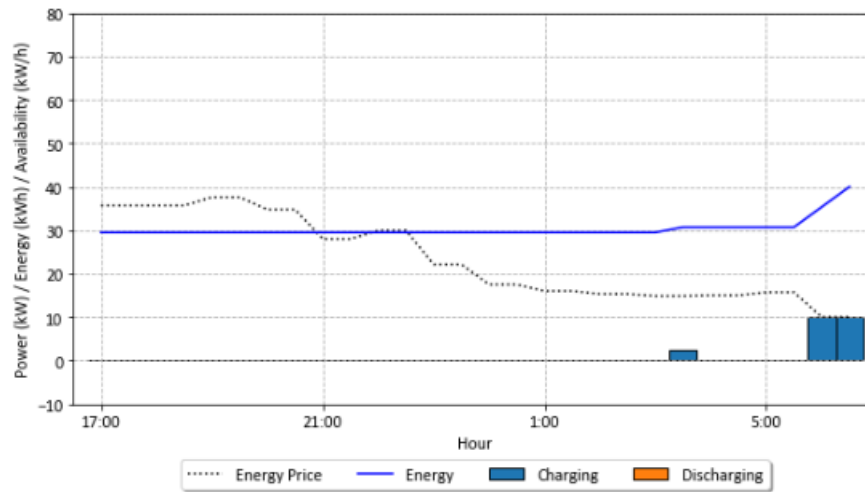


Figure 5.11: Scenario 2a Example Schedule: Energy Arbitrage with V1G Theoretical Benchmark Result

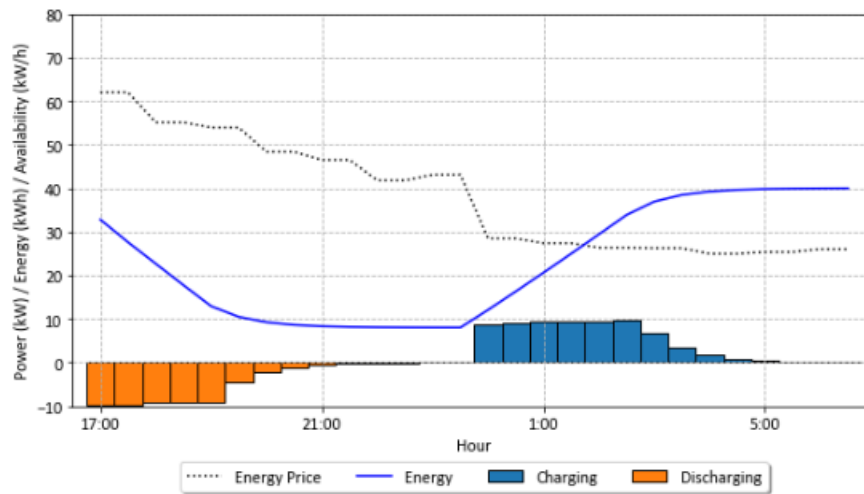


Figure 5.12: Scenario 2b Example Schedule: Energy Arbitrage with V2G produced with PPO Method

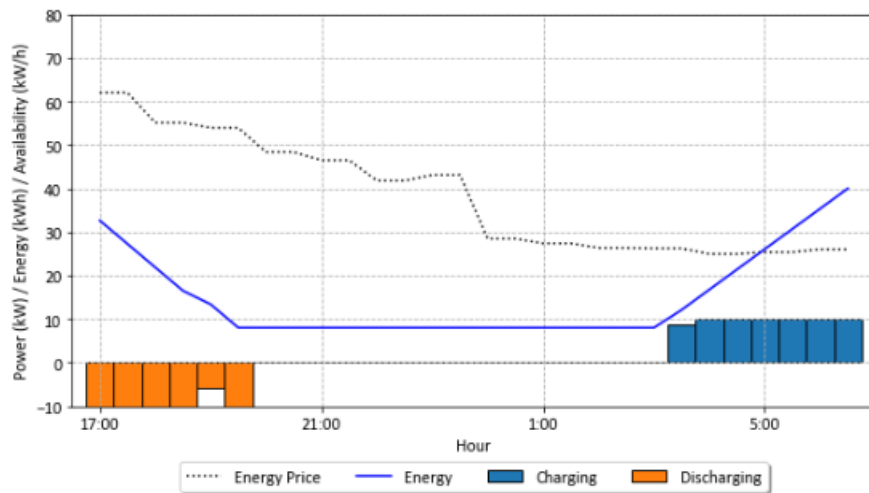


Figure 5.13: Scenario 2b Example Schedule: Energy Arbitrage with V2G Theoretical Benchmark Result

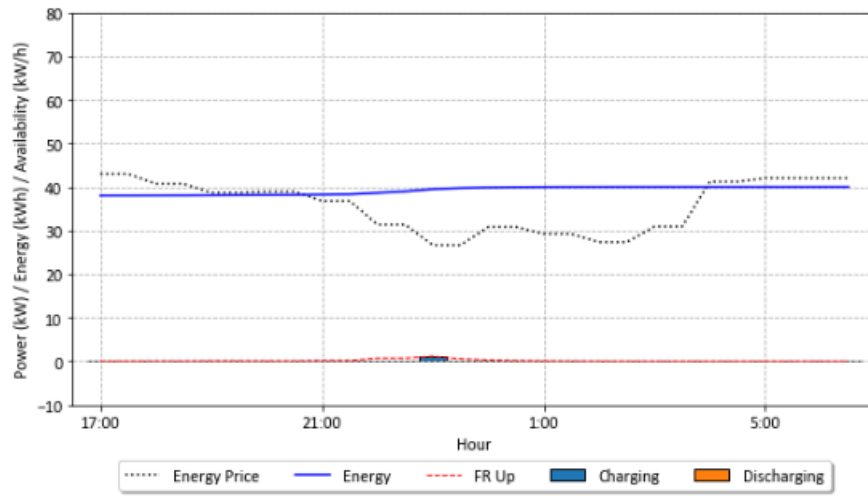


Figure 5.14: Scenario 3a Example Schedule: Energy Arbitrage and Balancing Services with V1G produced with PPO Method

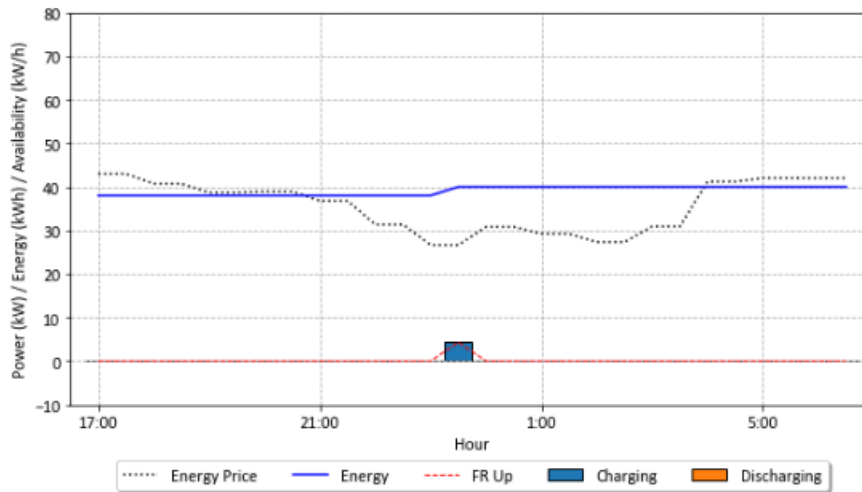


Figure 5.15: Scenario 3a Example Schedule: Energy Arbitrage and Balancing Services with V1G Theoretical Benchmark Result

Scenario 3b, which is the V2G charging mode with electricity and balancing services markets, is presented earlier in the Chapter; the PPO example schedule is shown in Figure 5.6 and the theoretical benchmark is shown in Figure 5.9. In general, the charging in the PPO schedule is more spread, however, the shape of the charging and discharging (in relation to electricity prices) is similar. This particular example resulted in the PPO schedule yielding 94% of the theoretical benchmark revenues.

5.7 Conclusions

This chapter has sought to answer the question of how to manage uncertainties in scheduling EV charging and discharging while participating in multiple markets. The rest of this thesis uses approaches that assume travel schedules and prices are known, either by performing analysis on historical data, or by generating a schedule for the following day given known travel requirements. In Chapter 4, the effects of uncertain trip lengths and balancing service practices are explored through a sensitivity analysis. In this chapter, a model-free real-time application of the multi-service EV charging operation to maximise revenue was successfully implemented, considering uncertain travel patterns and energy prices.

The scope of the case studies firstly compared the proposed method (PPO) to state-of-the-art methods (DQN and DDPG) and then to a theoretical benchmark. The shapes of the RL and theoretical benchmark charging schedules are comparable, as is the cumulative revenue over the 52 day test period (the RL approach achieving 94.1% of theoretical benchmark revenues).

The case studies applied the proposed method to different examined scenarios or modes of operation of the EVs in the fleet. This showed the method being applicable where charging was either one-directional (i.e. V1G or smart charging) or bidirectional (i.e. V2G), as well as either in one or multiple markets (i.e. energy only or energy and balancing services). In certain scenarios, the approach produced results that were closer to the theoretical benchmark, such as smart charging with energy arbitrage only and V2G with energy and balancing services.

The first benefit of the proposed method over conventional optimisation approach includes

being model-free, meaning the fleet operator need not know the mathematical models and technical parameters of each EV. Secondly, the uncertainties need not be well captured and modelled using representative stochastic and dynamic characteristics of the system. Thirdly, the RL schedules were produced within milliseconds, faster than solving a computationally intense optimisation considering multiple EVs with stochastic elements.

A limitation of this approach is that it is difficult to extend to incorporate network constraints. The algorithms used are also more complex than model-based approaches, have not been tested in practice (or demonstrated in real world applications on real chargers). This means fleet operators may be less willing to trust and adopt this technology.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

This thesis set out to close gaps in the literature, including the need to quantify potential revenues for EV users under current and future scenarios, investigate optimal EV operation to maximise revenues and address the uncertainties in such operation coming from unpredictable travel patterns and prices. It sought and presented ways to quantify the incentives for EV fleet operators to operate EVs, to capitalise on a future power system with higher renewable generation and higher FR prices, and to incorporate uncertainties into implementing charging schedules in the real world.

After providing some background to the current market framework in Chapter 2, Chapter 3 laid out several foundational mathematical models to quantify the maximum revenue EV fleets are able to earn under various examined scenarios. Real world data for 12 EV fleets taking part in GB-based demonstrator project E-Flex were used, along with real electricity and balancing service market prices. Results of detailed case studies showed that energy tariffs had a large impact on EV charging costs and that the TOU tariff was not always favourable. The most lucrative examined scenario was that of V2G, an export tariff and FR provision.

The central scenario from Chapter 3, namely the charging scenario where EV fleets operate in

V2G mode, optimising against the energy price while providing FR services was the scenario expanded upon in the next chapters of the thesis.

In Chapter 4, both the summer and winter seasons were modelled for the maintenance fleet, showing the effects of renewable generation on ancillary services prices and fleet revenue. Revenues for the inflexible (i.e. original) trips and the flexible trips across the summer and winter seasons were first compared using the maintenance fleet to model the four scenarios outlined in Section 4.2.3. Then, the difference between the maintenance and delivery fleets was investigated to show how driving patterns affect revenue in this approach. Lastly, some extreme weather days were analysed to show examples of potential maximum benefit from flexible trips. This is a way to demonstrate the major differences between fleets and seasons in an extreme case. The benefit of the flexible trips approach, scheduling charging and trips simultaneously, resulted in the equivalent additional annual revenues of £729 per EV.

Additional analysis was performed in this chapter to increase the robustness of the approach and the depth of the insights from the results. Firstly, a method was implemented to reduce battery cycling, as this is a common topic of discussion in the context of utilising EV batteries with V2G for service provision. Secondly, two sets of sensitivity analyses were performed on both the FR price and the traffic related conditions (acknowledging the fact that these factors had elements of uncertainty). A 25% reduction in FR price resulted in a reduction in revenues of a similar percentage. A simulated traffic event, leading to an hour's delay in trip time resulted in a 7% reduction in revenues. Finally, the equivalent CO₂ emissions avoided of EV fleet participation were calculated. These emissions were based on the assumption that the FR could be provided by the EV fleet instead of a CCGT. In a summer month, a fleet of 5,000 EVs would avoid one CCGT operating and producing 62,500 kg of CO₂.

Whereas in the thesis up to and including Chapter 4 assumed known trip information and services prices, Chapter 5 answered the question of how to deal with the uncertainties of these inputs. This is especially important when implementing EV fleet charging and trip scheduling and potentially implementing the work of this thesis in the real world.

Chapter 5 presents a new, model-free real-time application of the multi-service EV charging

operation to maximise revenue. It used the state-of-the-art Proximal Policy Optimisation algorithm, bench-marked against other state-of-the-art approaches (DQN and DDPG) and compared to the theoretical optimum. When run on a test period of one random day a week for a year, DQN achieved 70.0% of the theoretical benchmark, while DDPG achieved 80.1% and the proposed PPO approach was able to achieve 94.1%. Considering the benefits of the approach, including being model-free (no need for known model and parameters of the physical system) and accounting for the uncertainties in travel pattern and energy prices, this result is significant and shows promise for future application.

6.2 Future Work

6.2.1 Market Studies

Much research is needed to ensure that the market framework is aligned with the agenda to decarbonise the transport and energy systems. Most of this thesis assumes EV are price takers, and the market prices are not examined. In Chapter 4, future prices are projected based on the physical reduction in inertia from renewable energy uptake in the GB system leading to higher operational costs and hence balancing service prices. However, there are other areas where the value EVs bring, both in terms of cost but also in terms of carbon emission reduction, must be reflected in the markets. For example, by implementing V2G technology and charging EVs during times of high renewable energy output, less renewable energy needs to be built in order to meet renewable energy targets. This also applies to carbon emissions; EVs can reduce the carbon emissions of the energy sector by 'absorbing' more low carbon energy and discharging it to meet demand. Although the carbon market is seen as a way to potentially quantify and reward these benefits, as discussed in Chapter 3, the carbon market has too low a price at the moment to impact EV operation. This would be under the assumption EVs could participate in the market. So, further work is needed in this area to quantify and real value that EVs can bring to the energy system and to investigate ways to integrate these benefits into the market, whereby they can be rewarded.

This leads to the second important need for future work in this area, and that is to investigate and develop the regulatory framework for EV market participation. For instance, a minimum of 1MW of flexibility is currently needed to participate in most balancing services in GB. For DSO services, it is closer to 100kW or 0.5MW. If the market is to be competitive and encourage EV market participation (and hence grant incentives for the electrification of transport), there needs to be further research into the concerns of TSOs and DSOs in lowering this threshold. It is anticipated that the control, administrative and security burden of integrating so many distributed EVs would be difficult.

In the context of markets, future work on the basis of this thesis could include investigating and quantifying the value from offering other products. Other ancillary services could be considered, including synthetic inertia provision and reactive power provision, which could potentially enhance the business case for flexible EV fleets as well as for other demand-side response assets. Another interesting element is the effect of many EVs on the price for services (i.e. achieving market saturation). These studies are highly relevant in such a fast changing market climate.

6.2.2 Operational Enhancement

As new EVs enter the market and the sector continues to decarbonise, future work could include investigating the effect of battery size on costs for these different scenarios examined throughout this thesis, as well as higher rated V2G chargers. The effect of various scenarios explored in this thesis on battery degradation could also be investigated.

None of the capital costs have been investigated here and so future work could incorporate the cost of capital investment in larger batteries and / or higher rated chargers, and compare this against the annual cost savings available. As many of these charging strategies involve energy arbitrage, an investigation into the cost of increased battery cycling compared to the benefit in reduced costs and revenues earned would also be important.

The number of tariffs used in this thesis has been limited to those provided by trial fleets in

the data set used, or the Octopus Agile tariffs (calculated using the wholesale energy price). Future work could examine what an optimal tariff for EVs would look like, so as to incentivise off-peak charging (to not overburden the network). Also, the effect of utilisation of balancing services could be investigated, along with potential penalties for not providing the services when called on. For instance, given the uncertainty of EV arrival times and high penalties for under-delivery of balancing services, is it worth bidding a lower capacity than your fleet (e.g. 80%), to mitigate this risk?

Given the demonstrated value of optimal trip scheduling for EV fleets in Chapter 4, future work could develop this value quantification into an operational tool for fleet operators, considering uncertainties in driving patterns due to external factors such as traffic conditions, as well as renewable energy output. This will allow for minor adjustments to the schedule in real-time and considering changing conditions. Also, a wider range of fleet types and use cases, such as electric taxis or car-sharing fleets, could be considered. Certain fleets will prove more suited for this scheduling approach, and it will be important to identify them. Assumptions around fleet operations (e.g. travel windows) could be further investigated and refined, to test whether a wide range of commercial fleets could benefit. Furthermore, integrating non-commercial vehicles into the formulation, such as domestic EVs that are unlikely to change travel times but could provide frequency services when plugged in, would provide a comprehensive view of the potential system benefits of an electrified transportation sector.

6.2.3 Scale

With reference to all of the studies in the thesis, future work would also aim to investigate techniques to incorporate a larger number of vehicles. For the work in Chapter 4, this would need to be without compromising on the speed of reaching an optimal solution for charging and trip scheduling.

In order to extend the data-driven technique presented in Chapter 5, a multi-agent reinforcement learning technique could be deployed to allow for a fleet with a larger number of EVs. Other RL algorithms should be tested for suitability in this application.

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Appendix A

Data

The raw data collected as part of the EFlex trial [15] was in the form of GPS data of trips for each fleet vehicle in each trial fleet. This appendix presents a sample of trip data for the month of September 2021 for Fleet A.

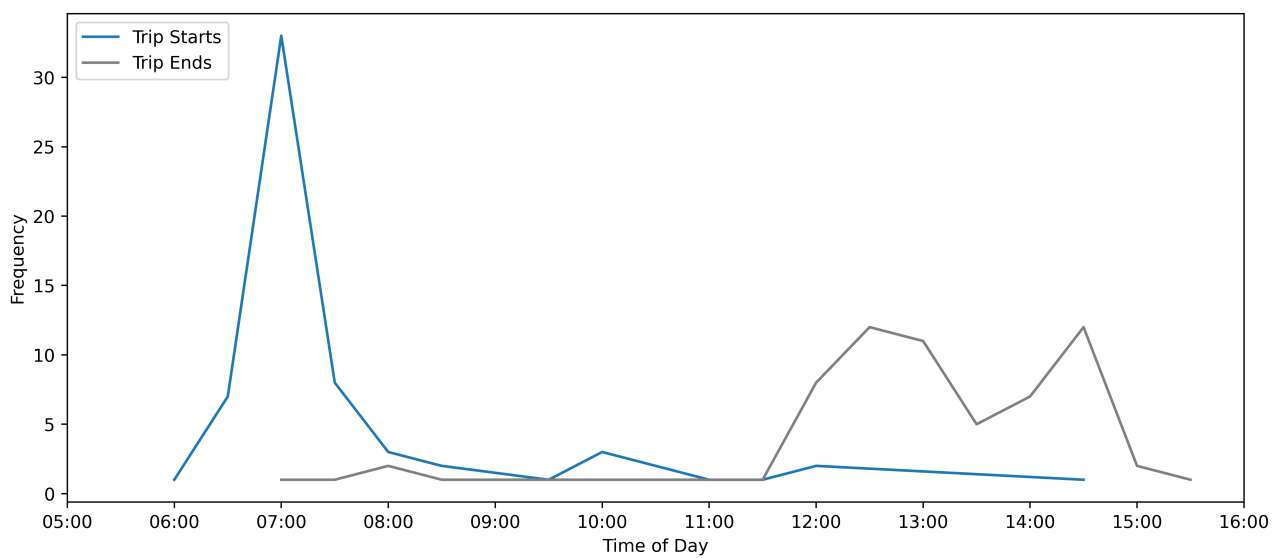


Figure A.1: Fleet A Sample Month: Start and End Trip Times

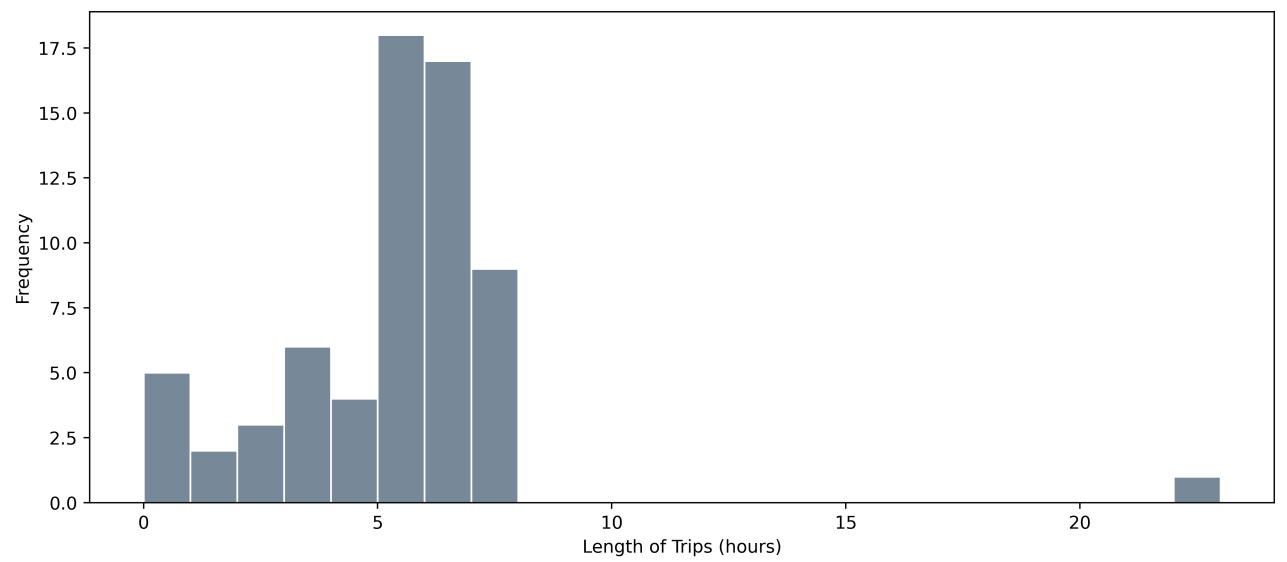


Figure A.2: Fleet A Sample Month: Trip Lengths

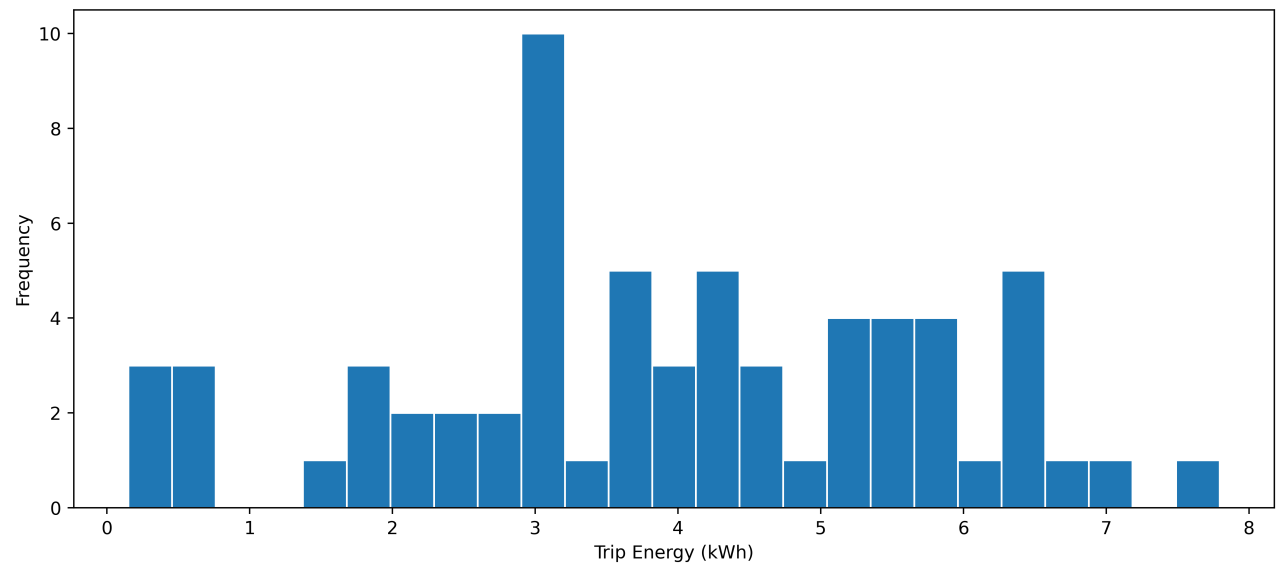


Figure A.3: Fleet A Sample Month: Trip Energy

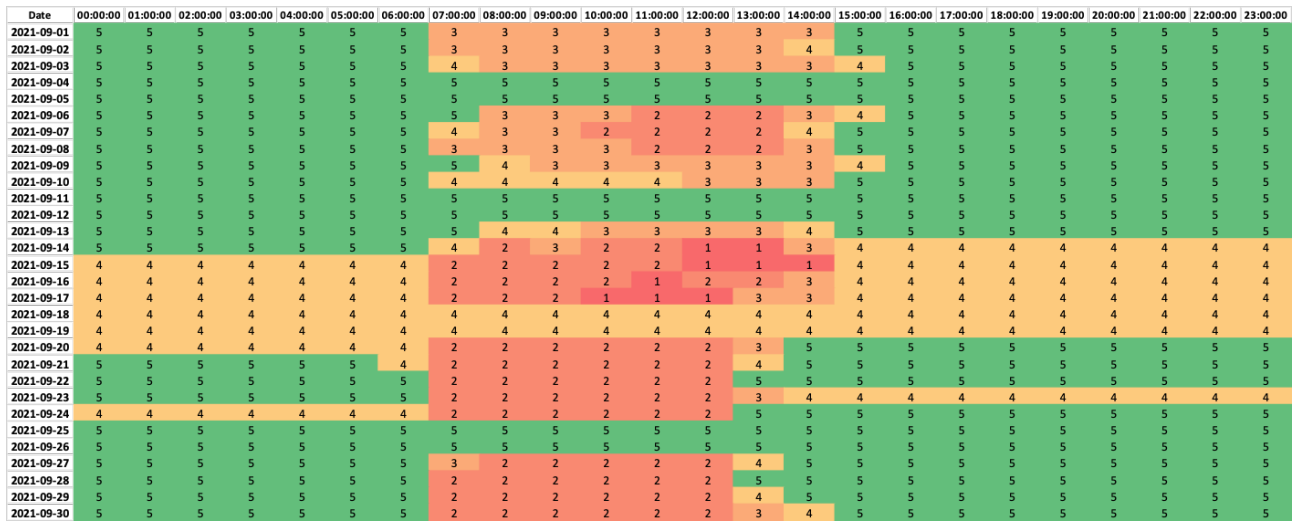


Figure A.4: Fleet A Sample Month: Availability

Figure A.4 shows a heat map of how many EVs in this fleet are connected every hour during the month of September 2021. The availability of the whole fleet (i.e. hours connected to the grid) is 85%. This means the EVs are connected and ready to provide grid services 85% of the total possible time.

Appendix B

Detailed Results for All Fleets

Here, the annual results tables for all examined scenarios for all fleets are included.

Table B.1: Fleet B Annual Results per EV with Current Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	105.17	105.17	-	-	147.53	756.38	-	3.27
2a: Energy (V1G)	74.06	74.06	-	-	120.74	756.38	-	10.00
2b: Energy (V2G)	74.06	74.06	-	-	119.13	756.38	0.00	10.00
3a: Energy and FR (V1G)	73.18	74.06	-	0.88	116.93	756.38	-	9.41
3b: Energy and FR (V2G)	-139.02	74.31	-	213.33	116.17	756.38	0.00	10.00
4a: Energy and Carbon (V1G)	79.49	74.06	5.43	-	108.58	756.38	-	10.00
4b: Energy and Carbon (V2G)	79.49	74.06	5.43	-	108.58	756.38	0.00	10.00
5a: Multi-Service (V1G)	78.67	74.06	5.48	0.88	109.69	756.38	0.00	10.00
5b: Multi-Service (V2G)	-133.53	74.13	5.49	213.14	109.75	756.38	0.00	10.00

Table B.2: Fleet B Annual Results per EV with TOU Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	219.70	219.70	-	-	147.53	756.38	-	3.27
2a: Energy (V1G)	173.73	173.73	-	-	119.35	756.38	-	10.00
2b: Energy (V2G)	166.72	166.72	-	-	118.49	946.29	164.25	10.00
3a: Energy and FR (V1G)	172.99	173.84	-	0.85	116.21	756.38	-	9.20
3b: Energy and FR (V2G)	-45.79	167.39	-	213.18	116.12	926.04	146.73	10.00
4a: Energy and Carbon (V1G)	179.34	173.76	5.58	-	111.57	756.38	-	10.00
4b: Energy and Carbon (V2G)	171.93	166.76	5.17	-	103.36	959.19	175.41	10.00
5a: Multi-Service (V1G)	178.68	173.85	5.68	0.85	113.60	756.38	-	10.00
5b: Multi-Service (V2G)	-40.23	167.37	5.49	213.10	109.82	936.86	156.09	10.00

Table B.3: Fleet B Annual Results per EV with TOU Import Tariff and TOU Export Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	219.70	219.70	-	-	147.53	756.38	-	3.27
2a: Energy (V1G)	173.73	173.73	-	-	119.35	756.38	-	10.00
2b: Energy (V2G)	-371.28	-371.28	-	-	33.83	4126.48	2914.79	10.00
3a: Energy and FR (V1G)	172.99	173.84	-	0.85	116.21	756.38	-	9.20
3b: Energy and FR (V2G)	-563.01	-366.96	-	196.04	37.32	3913.34	2730.45	10.00
4a: Energy and Carbon (V1G)	179.34	173.76	5.58	-	111.57	756.38	-	10.00
4b: Energy and Carbon (V2G)	-370.96	-371.12	0.17	-	3.43	4167.54	2950.31	10.00
5a: Multi-Service (V1G)	178.68	173.85	5.68	0.85	113.60	756.38	-	10.00
5b: Multi-Service (V2G)	-561.56	-367.11	1.27	195.73	25.51	3949.81	2761.99	10.00

Table B.4: Fleet C Annual Results per EV with Current Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	202.66	202.66	-	-	267.14	1369.31	-	8.56
2a: Energy (V1G)	202.66	202.66	-	-	237.99	1369.31	-	10.00
2b: Energy (V2G)	202.66	202.66	-	-	262.94	1369.31	0.00	10.00
3a: Energy and FR (V1G)	195.99	202.66	-	6.66	224.01	1369.31	-	5.00
3b: Energy and FR (V2G)	85.39	202.66	-	117.27	240.04	1369.31	0.00	7.50
4a: Energy and Carbon (V1G)	212.76	202.66	10.10	-	202.01	1369.31	-	10.00
4b: Energy and Carbon (V2G)	212.76	202.66	10.10	-	202.01	1369.31	0.00	10.00
5a: Multi-Service (V1G)	206.75	202.66	10.66	6.56	213.08	1369.31	-	5.00
5b: Multi-Service (V2G)	96.61	202.66	10.93	116.97	218.62	1369.31	0.00	6.18

Table B.5: Fleet C Annual Results per EV with TOU Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	387.07	387.07	-	-	267.14	1369.31	-	8.56
2a: Energy (V1G)	314.08	314.08	-	-	218.48	1369.31	-	10.00
2b: Energy (V2G)	308.83	308.83	-	-	220.95	1494.65	108.40	10.00
3a: Energy and FR (V1G)	312.44	314.56	-	2.12	216.42	1369.31	-	10.00
3b: Energy and FR (V2G)	198.40	309.78	-	111.39	219.08	1483.77	98.99	10.00
4a: Energy and Carbon (V1G)	324.63	314.10	10.53	-	210.59	1369.31	-	10.00
4b: Energy and Carbon (V2G)	319.12	308.85	10.27	-	205.35	1501.46	114.29	10.00
5a: Multi-Service (V1G)	323.13	314.59	10.65	2.11	212.93	1369.31	-	10.00
5b: Multi-Service (V2G)	209.07	309.81	10.55	111.28	211.04	1490.58	104.88	10.00

Table B.6: Fleet C Annual Results per EV with TOU Import Tariff and TOU Export Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	387.07	387.07	-	-	267.14	1369.31	-	8.56
2a: Energy (V1G)	314.08	314.08	-	-	218.48	1369.31	-	10.00
2b: Energy (V2G)	94.76	94.76	-	-	190.00	2895.07	1319.62	10.00
3a: Energy and FR (V1G)	312.44	314.56	-	2.12	216.42	1369.31	-	10.00
3b: Energy and FR (V2G)	-8.02	97.26	-	105.27	186.92	2837.58	1269.90	10.00
4a: Energy and Carbon (V1G)	324.63	314.10	10.53	-	210.59	1369.31	-	10.00
4b: Energy and Carbon (V2G)	103.17	94.84	8.33	-	166.54	2905.93	1329.02	10.00
5a: Multi-Service (V1G)	323.13	314.59	10.65	2.11	212.93	1369.31	-	10.00
5b: Multi-Service (V2G)	0.92	96.82	8.80	104.70	176.08	2855.84	1285.69	10.00

Table B.7: Fleet D Annual Results per EV with Current Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	79.36	79.36	-	-	120.36	640.23	-	6.14
2a: Energy (V1G)	65.86	65.86	-	-	102.22	640.23	-	10.00
2b: Energy (V2G)	65.86	65.86	-	-	102.22	640.23	0.00	10.00
3a: Energy and FR (V1G)	64.31	67.74	-	3.42	106.02	640.23	-	3.44
3b: Energy and FR (V2G)	-195.34	68.93	-	264.27	109.55	640.23	0.00	5.00
4a: Energy and Carbon (V1G)	70.95	65.88	5.08	-	101.55	640.23	-	10.00
4b: Energy and Carbon (V2G)	70.95	65.88	5.08	-	101.55	640.23	0.00	10.00
5a: Multi-Service (V1G)	69.54	67.75	5.21	3.41	104.10	640.23	-	3.44
5b: Multi-Service (V2G)	-189.94	68.79	5.35	264.08	106.92	640.23	0.00	5.00

Table B.8: Fleet D Annual Results per EV with TOU Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	156.14	156.14	-	-	120.36	640.23	-	6.14
2a: Energy (V1G)	124.30	124.30	-	-	104.16	640.23	-	10.00
2b: Energy (V2G)	117.37	117.37	-	-	101.24	830.49	164.55	10.00
3a: Energy and FR (V1G)	124.08	124.42	-	0.35	102.90	640.23	-	10.00
3b: Energy and FR (V2G)	-141.34	118.34	-	259.68	101.10	813.57	149.92	10.00
4a: Energy and Carbon (V1G)	129.35	124.31	5.04	-	100.79	640.23	-	10.00
4b: Energy and Carbon (V2G)	122.04	117.40	4.64	-	92.80	840.49	173.20	10.00
5a: Multi-Service (V1G)	129.14	124.43	5.06	0.34	101.15	640.23	-	10.00
5b: Multi-Service (V2G)	-136.41	118.30	4.87	259.58	97.28	820.23	155.68	10.00

Table B.9: Fleet D Annual Results per EV with TOU Import Tariff and TOU Export Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	156.14	156.14	-	-	120.36	640.23	-	6.14
2a: Energy (V1G)	124.30	124.30	-	-	104.16	640.23	-	10.00
2b: Energy (V2G)	-414.33	-414.33	-	-	25.71	4278.08	3146.38	10.00
3a: Energy and FR (V1G)	124.08	124.42	-	0.35	102.90	640.23	-	10.00
3b: Energy and FR (V2G)	-646.49	-407.66	-	238.83	36.76	3823.03	2752.80	10.00
4a: Energy and Carbon (V1G)	129.35	124.31	5.04	-	100.79	640.23	-	10.00
4b: Energy and Carbon (V2G)	-414.10	-414.13	0.03	-	0.55	4330.08	3191.35	10.00
5a: Multi-Service (V1G)	129.14	124.43	5.06	0.34	101.15	640.23	-	10.00
5b: Multi-Service (V2G)	-644.88	-407.89	1.47	238.47	29.46	3854.39	2779.93	10.00

Table B.10: Fleet E Annual Results per EV with Current Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	57.49	57.49	-	-	91.11	464.80	-	8.74
2a: Energy (V1G)	45.55	45.55	-	-	81.26	464.80	-	10.00
2b: Energy (V2G)	45.55	45.55	-	-	76.19	464.80	0.00	10.00
3a: Energy and FR (V1G)	43.05	45.55	-	2.49	77.75	464.80	-	3.00
3b: Energy and FR (V2G)	-192.28	45.55	-	237.84	77.75	464.80	0.00	3.00
4a: Energy and Carbon (V1G)	49.09	45.55	3.54	-	70.87	464.80	-	10.00
4b: Energy and Carbon (V2G)	49.09	45.55	3.54	-	70.87	464.80	0.00	10.00
5a: Multi-Service (V1G)	46.95	45.55	3.89	2.49	77.75	464.80	-	3.00
5b: Multi-Service (V2G)	-188.39	45.55	3.89	237.84	77.75	464.80	0.00	3.00

Table B.11: Fleet E Annual Results per EV with TOU Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	126.20	126.20	-	-	91.11	464.80	-	8.74
2a: Energy (V1G)	107.76	107.76	-	-	77.06	464.80	-	10.00
2b: Energy (V2G)	100.55	100.55	-	-	73.24	661.23	169.89	10.00
3a: Energy and FR (V1G)	107.37	107.84	-	0.45	75.37	464.80	-	10.00
3b: Energy and FR (V2G)	-134.60	101.05	-	235.65	74.09	640.97	152.37	10.00
4a: Energy and Carbon (V1G)	111.41	107.77	3.65	-	73.07	464.80	-	10.00
4b: Energy and Carbon (V2G)	103.78	100.57	3.22	-	64.44	674.33	181.22	10.00
5a: Multi-Service (V1G)	111.07	107.84	3.69	0.45	73.93	464.80	-	10.00
5b: Multi-Service (V2G)	-131.09	101.04	3.49	235.63	69.82	648.57	158.94	10.00

Table B.12: Fleet E Annual Results per EV with TOU Import Tariff and TOU Export Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	126.20	126.20	-	-	91.11	464.80	-	8.74
2a: Energy (V1G)	107.76	107.76	-	-	77.06	464.80	-	10.00
2b: Energy (V2G)	-385.62	-385.62	-	-	-6.75	3913.49	2982.75	10.00
3a: Energy and FR (V1G)	107.37	107.84	-	0.45	75.37	464.80	-	10.00
3b: Energy and FR (V2G)	-596.97	-380.27	-	216.70	4.36	3560.07	2677.10	10.00
4a: Energy and Carbon (V1G)	111.41	107.77	3.65	-	73.07	464.80	-	10.00
4b: Energy and Carbon (V2G)	-387.08	-385.44	-1.65	-	-32.95	3966.57	3028.66	10.00
5a: Multi-Service (V1G)	111.07	107.84	3.69	0.45	73.93	464.80	-	10.00
5b: Multi-Service (V2G)	-597.05	-381.06	-0.30	215.71	-5.88	3628.45	2736.23	10.00

Table B.13: Fleet F Annual Results per EV with Current Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	177.53	177.53	-	-	227.37	1199.52	-	5.82
2a: Energy (V1G)	177.53	177.53	-	-	216.79	1199.52	-	10.00
2b: Energy (V2G)	177.53	177.53	-	-	228.95	1199.52	0.00	10.00
3a: Energy and FR (V1G)	171.10	177.53	-	6.43	187.91	1199.52	-	2.61
3b: Energy and FR (V2G)	-134.16	177.53	-	311.69	204.98	1199.52	0.00	4.29
4a: Energy and Carbon (V1G)	185.69	177.53	8.16	-	163.14	1199.52	-	10.00
4b: Energy and Carbon (V2G)	185.69	177.53	8.16	-	163.14	1199.52	0.00	10.00
5a: Multi-Service (V1G)	180.06	177.53	8.83	6.30	176.63	1199.52	-	2.61
5b: Multi-Service (V2G)	-124.31	177.53	9.60	311.43	192.02	1199.52	0.00	4.48

Table B.14: Fleet F Annual Results per EV with TOU Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	350.64	350.64	-	-	227.37	1199.52	-	5.82
2a: Energy (V1G)	280.95	280.95	-	-	185.71	1199.52	-	10.00
2b: Energy (V2G)	273.92	273.92	-	-	184.12	1389.54	164.35	10.00
3a: Energy and FR (V1G)	279.98	281.14	-	1.16	181.78	1199.52	-	10.00
3b: Energy and FR (V2G)	-26.88	275.34	-	302.21	183.38	1371.19	148.48	10.00
4a: Energy and Carbon (V1G)	289.80	280.98	8.83	0.00	176.50	1199.52	-	10.00
4b: Energy and Carbon (V2G)	282.32	273.96	8.37	0.00	167.27	1416.18	187.39	10.00
5a: Multi-Service (V1G)	288.92	281.15	8.92	1.14	178.41	1199.52	-	10.00
5b: Multi-Service (V2G)	-17.99	275.18	8.77	301.94	175.33	1384.83	160.27	10.00

Table B.15: Fleet F Annual Results per EV with TOU Import Tariff and TOU Export Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	350.64	350.64	-	-	227.37	1199.52	-	5.82
2a: Energy (V1G)	280.95	280.95	-	-	185.71	1199.52	-	10.00
2b: Energy (V2G)	-358.31	-358.31	-	-	104.80	5225.42	3482.00	10.00
3a: Energy and FR (V1G)	279.98	281.14	-	1.16	181.78	1199.52	-	10.00
3b: Energy and FR (V2G)	-625.24	-351.02	-	274.23	119.49	4641.79	2977.22	10.00
4a: Energy and Carbon (V1G)	289.80	280.98	8.83	-	176.50	1199.52	-	10.00
4b: Energy and Carbon (V2G)	-354.56	-358.07	3.51	-	70.30	5266.13	3517.21	10.00
5a: Multi-Service (V1G)	288.92	281.15	8.92	1.14	178.41	1199.52	-	10.00
5b: Multi-Service (V2G)	-619.69	-351.48	5.37	273.57	107.37	4657.85	2991.11	10.00

Table B.16: Fleet G Annual Results per EV with Current Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	152.64	152.64	-	-	142.23	729.39	-	2.38
2a: Energy (V1G)	106.79	106.79	-	-	122.20	729.39	-	10.00
2b: Energy (V2G)	106.79	106.79	-	-	117.46	729.39	0.00	10.00
3a: Energy and FR (V1G)	102.91	106.79	-	3.88	119.72	729.39	-	10.00
3b: Energy and FR (V2G)	-181.20	106.79	-	287.99	121.52	729.39	0.00	10.00
4a: Energy and Carbon (V1G)	112.21	106.79	5.42	-	108.45	729.39	-	10.00
4b: Energy and Carbon (V2G)	112.21	106.79	5.42	-	108.45	729.39	0.00	10.00
5a: Multi-Service (V1G)	108.90	106.79	5.99	3.88	119.72	729.39	-	10.00
5b: Multi-Service (V2G)	-175.12	106.79	6.08	287.99	121.52	729.39	0.00	10.00

Table B.17: Fleet G Annual Results per EV with TOU Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	207.55	207.55	-	-	142.23	729.39	-	2.38
2a: Energy (V1G)	165.90	165.90	-	-	117.88	729.39	-	10.00
2b: Energy (V2G)	158.81	158.81	-	-	117.77	922.96	167.41	10.00
3a: Energy and FR (V1G)	165.25	166.03	-	0.78	115.96	729.39	-	10.00
3b: Energy and FR (V2G)	-124.66	160.04	-	284.71	119.55	902.70	149.90	10.00
4a: Energy and Carbon (V1G)	171.51	165.92	5.59	0.00	111.75	729.39	-	10.00
4b: Energy and Carbon (V2G)	163.93	158.84	5.09	0.00	101.86	953.50	193.83	10.00
5a: Multi-Service (V1G)	170.92	166.03	5.66	0.77	113.23	729.39	-	10.00
5b: Multi-Service (V2G)	-118.96	159.97	5.58	284.51	111.57	914.03	159.69	10.00

Table B.18: Fleet G Annual Results per EV with TOU Import Tariff and TOU Export Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	207.55	207.55	-	-	142.23	729.39	-	2.38
2a: Energy (V1G)	165.90	165.90	-	-	117.88	729.39	-	10.00
2b: Energy (V2G)	-449.08	-449.08	-	-	26.80	4688.93	3424.61	10.00
3a: Energy and FR (V1G)	165.25	166.03	-	0.78	115.96	729.39	-	10.00
3b: Energy and FR (V2G)	-701.81	-442.10	-	259.71	40.86	4174.97	2980.08	10.00
4a: Energy and Carbon (V1G)	171.51	165.92	5.59	-	111.75	729.39	-	10.00
4b: Energy and Carbon (V2G)	-449.19	-448.88	-0.31	-	-6.15	4739.36	3468.23	10.00
5a: Multi-Service (V1G)	170.92	166.03	5.66	0.77	113.23	729.39	-	10.00
5b: Multi-Service (V2G)	-700.16	-442.82	1.38	258.73	27.72	4205.51	3006.50	10.00

Table B.19: Fleet H Annual Results per EV with Current Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	61.57	61.57	-	-	58.46	302.80	-	3.75
2a: Energy (V1G)	44.05	44.05	-	-	50.05	302.80	-	10.00
2b: Energy (V2G)	44.05	44.05	-	-	47.46	302.80	0.00	10.00
3a: Energy and FR (V1G)	42.47	44.05	-	1.58	47.53	302.80	-	8.87
3b: Energy and FR (V2G)	-88.76	44.05	-	132.81	47.42	302.80	0.00	8.87
4a: Energy and Carbon (V1G)	46.20	44.05	2.15	-	43.06	302.80	-	10.00
4b: Energy and Carbon (V2G)	46.20	44.05	2.15	-	43.06	302.80	0.00	10.00
5a: Multi-Service (V1G)	44.84	44.05	2.37	1.58	47.39	302.80	-	8.87
5b: Multi-Service (V2G)	-86.39	44.05	2.37	132.81	47.40	302.80	0.00	8.87

Table B.20: Fleet H Annual Results per EV with TOU Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	84.62	84.62	-	-	58.46	302.80	-	3.75
2a: Energy (V1G)	66.66	66.66	-	-	47.17	302.80	-	10.00
2b: Energy (V2G)	60.50	60.50	-	-	46.12	461.35	137.14	10.00
3a: Energy and FR (V1G)	66.33	66.77	-	0.44	46.35	302.80	-	8.87
3b: Energy and FR (V2G)	-70.60	60.87	-	131.47	44.45	449.10	126.54	10.00
4a: Energy and Carbon (V1G)	68.90	66.67	2.22	-	44.52	302.80	-	10.00
4b: Energy and Carbon (V2G)	62.43	60.51	1.92	-	38.45	465.84	141.02	10.00
5a: Multi-Service (V1G)	68.60	66.77	2.26	0.43	45.19	302.80	-	10.00
5b: Multi-Service (V2G)	-68.49	60.88	2.10	131.46	42.01	453.59	130.42	10.00

Table B.21: Fleet H Annual Results per EV with TOU Import Tariff and TOU Export Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	84.62	84.62	-	-	58.46	302.80	-	3.75
2a: Energy (V1G)	66.66	66.66	-	-	47.17	302.80	-	10.00
2b: Energy (V2G)	-178.40	-178.40	-	-	-4.38	2418.16	1829.58	10.00
3a: Energy and FR (V1G)	66.33	66.77	-	0.44	46.35	302.80	-	8.87
3b: Energy and FR (V2G)	-295.11	-175.39	-	119.72	-3.77	2196.72	1638.05	10.00
4a: Energy and Carbon (V1G)	68.90	66.67	2.22	-	44.52	302.80	-	10.00
4b: Energy and Carbon (V2G)	-179.30	-178.30	-0.99	-	-19.84	2421.71	1832.65	10.00
5a: Multi-Service (V1G)	68.60	66.77	2.26	0.43	45.19	302.80	-	10.00
5b: Multi-Service (V2G)	-295.51	-175.43	-0.50	119.59	-9.82	2221.93	1659.85	10.00

Table B.22: Fleet I Annual Results per EV with Current Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	106.38	106.38	-	-	148.76	776.77	-	3.84
2a: Energy (V1G)	82.80	82.80	-	-	129.97	776.77	-	10.00
2b: Energy (V2G)	82.80	82.80	-	-	120.95	776.77	0.00	10.00
3a: Energy and FR (V1G)	78.64	82.80	-	4.16	122.77	776.77	-	4.12
3b: Energy and FR (V2G)	-180.06	82.80	-	262.87	122.72	776.77	0.00	4.12
4a: Energy and Carbon (V1G)	88.28	82.80	5.47	-	109.49	776.77	-	10.00
4b: Energy and Carbon (V2G)	88.28	82.80	5.47	-	109.49	776.77	0.00	10.00
5a: Multi-Service (V1G)	84.77	82.80	6.11	4.15	122.27	776.77	-	4.12
5b: Multi-Service (V2G)	-173.93	82.80	6.13	262.86	122.52	776.77	0.00	4.12

Table B.23: Fleet I Annual Results per EV with TOU Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	228.51	228.51	-	-	148.76	776.77	-	3.84
2a: Energy (V1G)	176.40	176.40	-	-	119.55	776.77	-	10.00
2b: Energy (V2G)	169.78	169.78	-	-	119.25	957.97	156.72	10.00
3a: Energy and FR (V1G)	175.70	176.58	-	0.87	116.57	776.77	-	8.83
3b: Energy and FR (V2G)	-89.56	170.56	-	260.11	120.15	939.32	140.59	10.00
4a: Energy and Carbon (V1G)	182.05	176.42	5.63	-	112.65	776.77	-	10.00
4b: Energy and Carbon (V2G)	175.02	169.83	5.20	-	103.97	984.31	179.50	10.00
5a: Multi-Service (V1G)	181.43	176.58	5.71	0.86	114.26	776.77	-	10.00
5b: Multi-Service (V2G)	-83.83	170.52	5.64	259.99	112.81	965.65	163.36	10.00

Table B.24: Fleet I Annual Results per EV with TOU Import Tariff and TOU Export Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	228.51	228.51	-	-	148.76	776.77	-	3.84
2a: Energy (V1G)	176.40	176.40	-	-	119.55	776.77	-	10.00
2b: Energy (V2G)	-363.14	-363.14	-	-	36.59	4397.53	3131.60	10.00
3a: Energy and FR (V1G)	175.70	176.58	-	0.87	116.57	776.77	-	8.83
3b: Energy and FR (V2G)	-597.59	-358.29	-	239.30	42.71	3966.15	2758.49	10.00
4a: Energy and Carbon (V1G)	182.05	176.42	5.63	-	112.65	776.77	-	10.00
4b: Energy and Carbon (V2G)	-362.77	-362.95	0.18	-	3.62	4442.49	3170.49	10.00
5a: Multi-Service (V1G)	181.43	176.58	5.71	0.86	114.26	776.77	-	10.00
5b: Multi-Service (V2G)	-595.85	-358.81	1.55	238.59	30.95	4016.01	2801.61	10.00

Table B.25: Fleet J Annual Results per EV with Current Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	182.06	182.06	-	-	244.72	1306.45	-	10.00
2a: Energy (V1G)	142.10	142.10	-	-	214.96	1306.45	-	10.00
2b: Energy (V2G)	142.10	142.10	-	-	205.65	1306.45	0.00	10.00
3a: Energy and FR (V1G)	135.10	142.10	-	6.99	201.35	1306.45	-	10.00
3b: Energy and FR (V2G)	-78.38	142.10	-	220.48	205.73	1306.45	0.00	10.00
4a: Energy and Carbon (V1G)	151.07	142.10	8.97	-	179.40	1306.45	-	10.00
4b: Energy and Carbon (V2G)	151.07	142.10	8.97	-	179.40	1306.45	0.00	10.00
5a: Multi-Service (V1G)	145.03	142.10	9.86	6.92	197.32	1306.45	-	10.00
5b: Multi-Service (V2G)	-68.30	142.10	9.99	220.38	199.74	1306.45	0.00	10.00

Table B.26: Fleet J Annual Results per EV with TOU Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	362.09	362.09	-	-	244.72	1306.45	-	10.00
2a: Energy (V1G)	278.55	278.55	-	-	198.40	1306.45	-	10.00
2b: Energy (V2G)	272.61	272.61	-	-	198.13	1468.85	140.46	10.00
3a: Energy and FR (V1G)	277.60	278.89	-	1.29	192.94	1306.45	-	10.00
3b: Energy and FR (V2G)	58.58	273.65	-	215.07	197.06	1453.30	127.00	10.00
4a: Energy and Carbon (V1G)	288.02	278.56	9.46	-	189.19	1306.45	-	10.00
4b: Energy and Carbon (V2G)	281.70	272.62	9.08	-	181.60	1486.63	155.83	10.00
5a: Multi-Service (V1G)	287.14	278.88	9.53	1.27	190.50	1306.45	-	10.00
5b: Multi-Service (V2G)	68.20	273.58	9.43	214.81	188.53	1471.07	142.38	10.00

Table B.27: Fleet J Annual Results per EV with TOU Import Tariff and TOU Export Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	362.09	362.09	-	-	244.72	1306.45	-	10.00
2a: Energy (V1G)	278.55	278.55	-	-	198.40	1306.45	-	10.00
2b: Energy (V2G)	-207.11	-207.11	-	-	132.03	4349.77	2632.17	10.00
3a: Energy and FR (V1G)	277.60	278.89	-	1.29	192.94	1306.45	-	10.00
3b: Energy and FR (V2G)	-402.62	-202.88	-	199.74	131.27	4069.66	2389.90	10.00
4a: Energy and Carbon (V1G)	288.02	278.56	9.46	-	189.19	1306.45	-	10.00
4b: Energy and Carbon (V2G)	-202.10	-206.93	4.84	-	96.81	4380.82	2659.02	10.00
5a: Multi-Service (V1G)	287.14	278.88	9.53	1.27	190.50	1306.45	-	10.00
5b: Multi-Service (V2G)	-396.45	-203.39	5.95	199.00	119.01	4099.36	2415.58	10.00

Table B.28: Fleet K Annual Results per EV with Current Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	144.48	144.48	-	-	171.93	860.37	-	5.01
2a: Energy (V1G)	88.87	88.87	-	-	147.46	860.37	-	10.00
2b: Energy (V2G)	88.87	88.87	-	-	138.63	860.37	0.00	10.00
3a: Energy and FR (V1G)	84.40	88.87	-	4.47	139.92	860.37	-	2.50
3b: Energy and FR (V2G)	-29.16	88.87	-	118.04	139.99	860.37	0.00	2.50
4a: Energy and Carbon (V1G)	95.31	88.87	6.44	-	128.81	860.37	-	10.00
4b: Energy and Carbon (V2G)	95.31	88.87	6.44	-	128.81	860.37	0.00	10.00
5a: Multi-Service (V1G)	91.39	88.87	6.99	4.47	139.80	860.37	-	2.50
5b: Multi-Service (V2G)	-22.17	88.87	6.99	118.04	139.90	860.37	0.00	2.50

Table B.29: Fleet K Annual Results per EV with TOU Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	253.44	253.44	-	-	171.93	860.37	-	5.01
2a: Energy (V1G)	201.63	201.63	-	-	138.36	860.37	-	10.00
2b: Energy (V2G)	195.47	195.47	-	-	138.89	1018.57	136.83	10.00
3a: Energy and FR (V1G)	200.58	201.87	-	1.29	134.86	860.37	-	7.01
3b: Energy and FR (V2G)	81.20	195.98	-	114.79	136.91	1006.65	126.52	10.00
4a: Energy and Carbon (V1G)	208.20	201.66	6.55	-	130.91	860.37	-	10.00
4b: Energy and Carbon (V2G)	201.73	195.49	6.24	-	124.87	1021.46	139.32	10.00
5a: Multi-Service (V1G)	207.23	201.87	6.62	1.26	132.45	860.37	-	10.00
5b: Multi-Service (V2G)	87.81	195.97	6.53	114.69	130.65	1009.54	129.01	10.00

Table B.30: Fleet K Annual Results per EV with TOU Import Tariff and TOU Export Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	253.44	253.44	-	-	171.93	860.37	-	5.01
2a: Energy (V1G)	201.63	201.63	-	-	138.36	860.37	-	10.00
2b: Energy (V2G)	-36.99	-36.99	-	-	81.32	2708.99	1598.87	10.00
3a: Energy and FR (V1G)	200.58	201.87	-	1.29	134.86	860.37	-	7.01
3b: Energy and FR (V2G)	-139.67	-34.55	-	105.13	80.91	2583.19	1490.07	10.00
4a: Energy and Carbon (V1G)	208.20	201.66	6.55	-	130.91	860.37	-	10.00
4b: Energy and Carbon (V2G)	-33.87	-36.93	3.06	-	61.13	2718.79	1607.34	10.00
5a: Multi-Service (V1G)	207.23	201.87	6.62	1.26	132.45	860.37	-	10.00
5b: Multi-Service (V2G)	-135.86	-34.83	3.67	104.70	73.38	2605.58	1509.43	10.00

Table B.31: Fleet L Annual Results per EV with Current Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	32.32	32.32	-	-	39.91	218.41	-	10.00
2a: Energy (V1G)	32.32	32.32	-	-	38.68	218.41	-	10.00
2b: Energy (V2G)	32.32	32.32	-	-	41.33	218.41	0.00	10.00
3a: Energy and FR (V1G)	31.17	32.32	-	1.17	35.75	218.41	-	3.36
3b: Energy and FR (V2G)	-241.67	32.32	-	273.99	38.39	218.41	0.00	10.00
4a: Energy and Carbon (V1G)	33.89	32.32	1.57	-	31.41	218.41	-	10.00
4b: Energy and Carbon (V2G)	33.89	32.32	1.57	-	31.41	218.41	0.00	10.00
5a: Multi-Service (V1G)	32.87	32.32	1.68	1.15	33.71	218.41	-	3.36
5b: Multi-Service (V2G)	-239.78	32.32	1.86	273.98	37.19	218.41	0.00	10.00

Table B.32: Fleet L Annual Results per EV with TOU Import Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	60.25	60.25	-	-	39.91	218.41	-	10.00
2a: Energy (V1G)	49.35	49.35	-	-	33.80	218.41	-	10.00
2b: Energy (V2G)	42.07	42.07	-	-	30.41	418.66	173.20	10.00
3a: Energy and FR (V1G)	49.19	49.40	-	0.21	33.41	218.41	-	10.00
3b: Energy and FR (V2G)	-229.17	42.42	-	271.59	30.11	398.41	155.68	10.00
4a: Energy and Carbon (V1G)	51.01	49.36	1.63	-	32.61	218.41	-	10.00
4b: Energy and Carbon (V2G)	43.27	42.09	1.17	-	23.61	432.77	185.41	10.00
5a: Multi-Service (V1G)	50.85	49.39	1.65	0.21	32.93	218.41	-	10.00
5b: Multi-Service (V2G)	-227.76	42.49	1.37	271.61	27.31	406.00	162.25	10.00

Table B.33: Fleet L Annual Results per EV with TOU Import Tariff and TOU Export Tariff

Scenario	Total Cost (£)	Energy Cost (£)	Carbon Cost (£)	FR Revenue (£)	CO ₂ Emissions (kg)	Energy Imported (kWh)	Energy Exported (kWh)	Peak Demand (kW)
1: Dumb Charging	60.25	60.25	-	-	39.91	218.41	-	10.00
2a: Energy (V1G)	49.35	49.35	-	-	33.80	218.41	-	10.00
2b: Energy (V2G)	-430.87	-430.87	-	-	-58.28	3706.07	3016.49	10.00
3a: Energy and FR (V1G)	49.19	49.40	-	0.21	33.41	218.41	-	10.00
3b: Energy and FR (V2G)	-675.25	-424.99	-	250.27	-51.47	3225.76	2601.05	10.00
4a: Energy and Carbon (V1G)	51.01	49.36	1.63	-	32.61	218.41	-	10.00
4b: Energy and Carbon (V2G)	-434.88	-430.68	-4.19	-	-83.95	3751.53	3055.79	10.00
5a: Multi-Service (V1G)	50.85	49.39	1.65	0.21	32.93	218.41	-	10.00
5b: Multi-Service (V2G)	-678.08	-425.46	-2.95	249.67	-59.11	3269.11	2638.55	10.00