## *Towards Smarter Electric Vehicle Charging with Low Carbon Smart Grids: Pricing and Control.*

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# Towards Smarter Electric Vehicle Charging with Low Carbon Smart Grids: Pricing and Control

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A Thesis presented for the degree of
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*This thesis is dedicated to*

The amazing people that have inspired me to continue challenging my knowledge and skills: my dear husband and my parents

*and*

all the academics and sponsors that believed in my PhD project

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**Abstract:** Environmental and political directions indicate transition to a decarbonised transportation system is necessary as it is one of the most pollutant sectors regarding greenhouse gas emissions. Research in Demand Side Management suggests that its tools are the most cost-effective option for improving the performance of the grid without incurring into high infrastructure investments, hence reducing the payback for start-ups in the sector. This Thesis proposes solutions to tackle 5 objectives around this area of research: 1-2 are related to developing a demand response pricing and EV smart charging strategies, 3-4 are related to developing a multi-objective charging scheme in order to ensure fairness and reduction of $CO_2$eq emissions, and 5 is related to testing parameters of EV charging to understand future improvements and limitations in the proposed models. Chapter 3, that tackles objectives 1-2, proposes a data-driven optimisation algorithm with pricing and control modules that communicate with each other to achieve a successful integration with the grid by charging at the right price and expected time. The results show customers can be positively engaged with pricing signals while providing support to the grid. Chapter 4, which tackles objectives 3-4, proposes a multi-objective EV charging formulation that include perspectives of EV users, a carbon regulator and a charging station operator. The multi-objective formulation is solved with a genetic algorithm in order

to find the fairest and the greenest solution. Results which are evaluated using different scenarios show different weights to each objective function can differ based on the charging location and EV charging availability. Finally, Chapter 5 which tackles objective 5, shows a sensitivity analysis where improvements in revenues, reduction of carbon emissions and bidding capacity depend on the evaluation of EV users' parameters, and the charging station control and sizing.

# Declaration

The work in this thesis is based on research carried out in the Department Engineering at Durham University. No part of this thesis has been submitted elsewhere for any degree or qualification.

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*"You cannot hope to build a better world without improving the individuals. To that end, each of us must work for his own improvement and, at the same time, share a general responsibility for all humanity, our particular duty being to aid those to whom we think we can be most useful."*

— from *Pierre Curie: With Autobiographical Notes by Marie Curie (1963) by Marie Curie, as translated by Charlotte Kellogg and Vernon Lyman Kellogg, p. 83*

# Contents

# List of Figures

# List of Tables



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# Nomenclature

## Constants

| | |
|---|---|
| $\alpha$ | Weight assigned to objective of EV users |
| $\beta$ | Weight assigned to objective of the carbon regulator |
| $\beta_{0t}$ | Intercept coefficient of linear regression |
| $\beta_{1t}$ | Slope coefficient of linear regression |
| $\delta$ | Expected revenue margin from participating in balancing services |
| $\gamma$ | Weight assigned to objective of the charging station operator |
| $a_{i,t}$ | Maximum charging rate of both an EV $i$ and the charging station pole (kW) |
| $ar$ | EV arrival time |
| $av_{i,t}$ | Availability of EV $i$ at the charging station pole in hour $t$ |
| $b_{i,t}$ | Minimum charging rate of both an EV $i$ and the charging station pole in hour $t$ (kW) |
| $c_{gv}$ | Total costs from balancing services and EV charging with G2V capability (£) |
| $c_i$ | Energy bill of EV $i$ (£) |
| $c_t$ | Charging operator costs in hour $t$ (£) |

| | |
|---|---|
| $c_{vg}$ | Total costs from balancing services and EV charging with V2G capability (£) |
| $ca_{i,t}$ | Carbon allowance per EV ($gCO_2eq/kWh$) |
| $cf_{i,0}$ | Carbon factor equivalence when an EV arrives at the charging station ($gCO_2eq$) |
| $cg_t$ | Energy grid costs in hour $t$ (£) |
| $cr_{m,t}$ | Carbon factor per fuel type ($gCO_2eq/kWh$) |
| $CS$ | Goal of the charging station operator |
| $CS_{max}$ | Maximum value of the objective of the charging station operator |
| $ctax_t$ | Carbon tax per kilowatt-hour (£ per $gCO_2eq/kWh$) |
| $d_{s,j}$ | Distance for each objective function $s$ and individual $j$ |
| $de$ | EV departure time |
| $e_{m,t}$ | Energy generation by fuel type (kWh) |
| $ef$ | Charging efficiency |
| $egcf_a$ | Hourly electricity grid carbon factor target ($gCO_2eq/kWh$) |
| $egcf_t$ | Hourly electricity grid carbon factor ($gCO_2eq/kWh$) |
| $egcf_l$ | Lower limit of electricity grid carbon factor |
| $egcf_u$ | Upper limit of electricity grid carbon factor |
| $EV$ | Objective of EV users |
| $EV_{max}$ | Maximum value of the objective of EV users |
| $evcf_{i,t}$ | Hourly EV carbon factor ($gCO_2eq$) |
| $f_{s,j}(\alpha_j,\ \beta_j, \gamma_j)$ | Space of objective functions of goal $s$ and chromosome $j$ |

| | |
|---|---|
| $f_t$ | Function of variations between $egcf_t$ and $egcf_a$ |
| $fl_{s,j}$ | Best possible solution available for each objective function $s$ and individual $j$ within a generation |
| $fu_{s,j}$ | Worst possible solution available for each objective function $s$ and individual $j$ within a generation |
| $g$ | Green solution with the lowest $CO_2$eq emissions based on the EV charging schedule |
| $h_t$ | High classification level |
| $i$ | Individual EV available for charging, $i \in I$ |
| $j$ | Chromosome in genetic algorithm ($j \in J$) |
| $k$ | Chromosome in genetic algorithm ($k \in J$) |
| $m$ | Fuel type, $m \in M$ |
| $m_t$ | High classification level |
| $n$ | Number of solar panels at the charging station |
| $p_t^*$ | Optimum price in hour $t$ (£/kWh) |
| $P_{i,t}$ | Solar power available to charge EV $i$ in time $t$ (kWh) |
| $p_t$ | Historical price in hour $t$ (£/kWh) |
| $pd_t$ | Energy price for demand turn down in hour $t$ (£/kWh) |
| $pf$ | Energy price including optimum price, demand turn down and up price incentives in a day (£/kWh) |
| $pgd_t$ | Price to send to auctions for demand turn down balancing services (£/kWh) |

| | |
|---|---|
| $pgu_t$ | Price to send to auctions for demand turn up balancing services (£/kWh) |
| $pm_t$ | Price for selling energy from EV users in carbon markets (£/kWh) |
| $Ps_t$ | Power generation per solar panel (kWh) |
| $pu_t$ | Energy price for demand turn up in hour $t$ (£) |
| $q^*_{i,t}$ | Optimum charging rate of EV $i$ in hour $t$ (kWh) |
| $Q^*_t$ | Optimum energy demand in hour $t$ (kWh) |
| $q_{i,t}$ | Charging rate of EV $i$ in hour $t$ (kWh) |
| $q^+_{i,t}$ | Positive charging rate of EV $i$ in time $t$ (kWh) |
| $q^-_{i,t}$ | Negative charging rate of EV $i$ in time $t$ (kWh) |
| $Q_t$ | Historical energy demand in hour $t$ (kWh) |
| $Qd_t$ | Turn down energy bidding (kWh) |
| $Qu_t$ | Turn up energy bidding (kWh) |
| $R$ | Goal of the carbon regulator |
| $r_{gv}$ | Total revenues from balancing services and EV charging with G2V capability (£) |
| $R_{max}$ | Maximum value of the objective of the carbon regulator |
| $r_{s,j}$ | Ranking value assigned to objective function $s$ and individual $j$ |
| $r_t$ | Revenues in hour $t$ (£) |
| $r_{vg}$ | Total revenues from balancing services and EV charging with V2G capability (£) |
| $rp$ | Solution with minimum ranking sum from the set of individuals in the pareto frontier |

| | |
|---|---|
| $s$ | Objective function in genetic algorithm ($s \in 3$) |
| $soc_{i,0}$ | State of charge when an EV arrives at the charging station (kWh) |
| $soc_{i,t}$ | State of charge of EV $i$ in hour $t$ (kWh) |
| $socf_i$ | Final state of charge of EV $i$ during a charging schedule (kWh) |
| $soci_i$ | Initial state of charge of EV $i$ during a charging schedule (kWh) |
| $te$ | Final hour for demand turn up balancing services in a day |
| $tf$ | Final hour for demand turn down balancing services in a day |
| $ti$ | Initial hour for demand turn down balancing services in a day |
| $tj$ | Initial hour for demand turn up balancing services in a day |
| $trip_i$ | Trip requirements for EV $i$ (kWh) |
| $u_{1t}$ | Utilities for demand turn down balancing services in hour $t$ (£) |
| $u_{2t}$ | Utilities for demand up balancing services in hour $t$ (£) |
| $u_t$ | Utilities in hour $t$ (£) |
| $w_i$ | Battery capacity of an EV $i$ (kWh) |
| $x_t$ | Energy demand values within positive utilities in hour $t$ (kWh) |
| $y_{i,t}$ | Charging rate limits of an EV $i$ in time $t$ (kW) |
| $z_{i,t}$ | Charging rate limits of a charging station pole assigned to EV $i$ in time $t$ (kW) |

# Chapter 1

# Introduction

## 1.1 Research Relevance

Nowadays, there are concerns about environmental issues and energy sustainability, as recent temperature trends show that temperature has been rising every decade by 0.18° C since 1981 [1]. Therefore, it is critical that countries around the globe develop strategies to tackle climate change and with detailed approaches in different sectors, for instance in the transport sector, which is the end-use sector with highest influence on $CO_2$ emissions with a total of 37% impact [2]. During COP26 Conference in Glasgow in 2021, countries declared their compromise towards having "all sales of new cars and bans being zero emission by 2040, and by 2035 in leading markets" [3]. For this reason, the UK has set a target of reducing Green House Gas emissions by 78% by 2035, relative to 1990 levels [4]. One countermeasure of this goal is to promote the adoption of ultra-low emission vehicles, such as Electric Vehicles (EVs), to help cut down emissions and air pollution. In fact, Point 4 of the ten point plan for a green industrial revolution in the UK states that to support the transition to zero emissions vehicles sales of new diesel and petrol vehicles will end by 2030 [5].

Mexico is also looking forward to take action into making a sustainable world for everyone. The Energy Reform, which started in 2013, establishes these general goals on its vision; to increase share of power generation by clean energy from 21% to

25% by 2015, 30% by 2021 and 35% by 2024, to reduce Green House Gas (GHG) emissions by 22% by 2030. Also to reduce black carbon emissions by 51% by the same year [6]. Mexico expects to have 20% of hybrid vehicle stock by 2040, in comparison to the situation today where 95% of passenger vehicles have combustion engines as described in the Mexico Energy Outlook. The transition to this future scenario offers challenges to the strategic and reliable distribution of electricity to automobiles and production of hybrid and electric vehicles. We can see here that similar general concerns regarding usage of EV's in the UK are also applicable to Mexico. AMIA, Mexican Association of the Mexican Automobile Industry, and CFE, Federal Commission of Electricity, are currently working together to promote hybrid and electrical vehicles as well the usage of charging stations [7]. In fact, BMW has started a program for creation of charging stations in collaboration with General Electric and Schneider Electric in order to prepare the required infrastructure for the deployment of EVs in Mexico [8]. However, there exist two major challenging issues around EVs that need solving:

1. Are EVs Really Green? EVs are charged using UK electricity, but about 35% (on average) of energy in the UK based on historical generation from January 1 - March 27, 2022 was generated from fossil fuels [9]. In addition, several stakeholders are concerned about emerging problems caused by EVs, such as carbon emission and their charging burden to power grids particularly at peak time.

2. EVs' Range Anxiety: EV users (or potential customers) fear that the EVs won't have enough stored energy to handle their daily driving needs, e.g., when they have to pick up children from school, the battery might not have enough stored energy to ensure the range.

The mission of this EVzero project developed at the Engineering Department in Durham University is: 'not only to empower future EVs with zero lifecycle emissions by integrating renewable energy, but also to reduce overblown range anxiety by developing EV charging system'. Thus, the aim of this Thesis is to develop and demonstrate how EV charging systems can be integrated with demand responsive mechanisms while reducing $CO_2$ accounted from EV charging. This research is part of one work package of the EVzero project, which requires a study of Demand Side Management (DSM) strategies. The principal objective of this study is to analyse supply of the grid and demand of end users (EVs) so that optimal systems operations are considered and ensured. Some benefits DSM studies are minimisation of costs, grid efficiency and stability, usage of renewable energy sources and participation of customers in pricing schemes [10; 11].

The research work in this Thesis will contribute to the area of smart charging using Demand Side Management strategies to integrate with renewable generation. This will provide solutions to the demand of knowledge required so that Mexico and the private industry can work together to achieve a significant impact in the goals indicated in the Energy Reform. The collaboration with leading Research with applications of Demand Side Management strategies in the EVzero project at Durham University, translates into solutions of future needs from the world leaders of this technology and research, that are key for Mexico's and UK's future progress.

## 1.2 Thesis Objectives

To support the decarbonisation in the commercial transportation sector. This thesis will focus on providing Demand Side Management solutions in EV charging schemes to enhance integration of renewable energy. Thus, specific goals to address are defined as follows,

- ***Objective 1:*** to design a pricing scheme that can influence EV drivers to participate in balancing services with the following basic aspects: economical operation of the charging station, effective measurement of charging behaviour relationship with price, auction based mechanism compliant with UK balancing services market and dynamic pricing with expected real time outputs.

- ***Objective 2:*** to design an EV charging control planning scheme to account for bidding and EV charging with the following aspects: variable integration of charging technology (both unidirectional and bidirectional), economical charging limits to ensure financial feasibility of charging transactions and stochastic driver behaviour (arrivals, departures and trips)

- ***Objective 3:*** to design a control scheme for EV charging to reduce carbon emissions with the following considerations: EV user charging station selection to ensure bill savings, regulator carbon factor penalty to limit charging during carbon intensive periods, carbon tax based pricing and transaction scheme that ensures benefits for EV users and the charging operator.

- ***Objective 4:*** to design a multi-objective optimisation approach to ensure fairness between all objectives and evaluate the trade-offs between all stakeholders involved as well as the potentials of EV technology to minimise carbon emissions in smart EV charging schemes.

- ***Objective 5:*** to analyze what parameters can improve the performance of a charging station operator in terms of $CO_2$eq emissions, bidding capacity to be used in market auctions, revenues and costs for both EV users and the charging operator.

## 1.3 Thesis Outline

This Thesis starts with the overview of basic concepts and relevant research in the area of Demand Side Management and EV charging techniques in Chapter 2. Then, Chapter 3 presents contributions using demand response pricing schemes and EV charging bidding optimisation that together address objectives 1-2. Chapter 4, presents a multi-objective optimisation approach with an innovative solving method that ensures fairness and reduction of carbon emissions which address objectives 3-4. Objective 5 is addressed in Chapter 5, where a sensitivity analysis is studied to show impacts when improving control or when designing the size of a charging station operator. To sum up all contributions, results and future research of work, Chapter 6 presents conclusions of the overall Thesis.

## 1.4 Thesis Publications

The following titles of publications are potential publishable manuscripts to be developed. Two manuscripts have already been published. The list of publications is as follows,

- Chapter 3:

    1. Integration of Electric Vehicles with Low Carbon Smart Grids: a Survey. To be submitted to Renewable and Sustainable Energy Reviews. Monica Hernandez Cedillo and Hongjian Sun.

- Chapter 4:

    1. Data-driven Pricing and Control for Low Carbon V2G Charging Station with Balancing Services. Published in IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids, 11-13 November 2020. Monica Hernandez Cedillo and Hongjian Sun.

    2. Dynamic Pricing and Control for EV Charging Station with Solar Generation. Published in Journal: Joint Special Issue on "Pathway to achieve carbon peak and carbon neutrality in transportation sector" (Applied Energy, Elsevier). Monica Hernandez Cedillo, Hongjian Sun and Jing Jiang.

- Chapter 5:

    1. Multi-objective V2G Charging Optimisation to Ensure Fairness and Reduction of Carbon Emissions. Definition of journal submission is pending.

Monica Hernandez Cedillo, Pedro Alberto Martinez Castro and Hongjian Sun.

# Chapter 2

# Literature review

## 2.1 Introduction

The Paris Agreement has put out one of the calls for efforts of many nations towards the climate change objective of maintaining a global temperature increment below 2°C above pre-industrial levels for the current century, and even limit to 1.5°C if possible [12]. As a consequence, countries such as the UK and Mexico have established several targets for reducing greenhouse gas (GHG) emissions. The UK aims to reduce GHG emissions by at least 80% by 2050, compared to 1990 levels [13]. Mexico looks for the goal of reducing these emissions by 50% by 2050, relative to 2000 levels [14]. However, these ambitious targets require precise and efficient actions that can produce the desired results.

In order to accomplish the goals described before, improvement on specific sectors is needed, one critical focus for development is in the transportation sector which represents about a quarter of total $CO_2$ emissions (included in GHG emissions) [15]. Recent studies have focused on developing efforts to enhance the deployment of electric vehicles (EVs) which are a promising and greener alternative in this sector compared to vehicles with internal combustion engines. In fact, the electric motor was initially invented before the internal combustion engine [16], the question is:

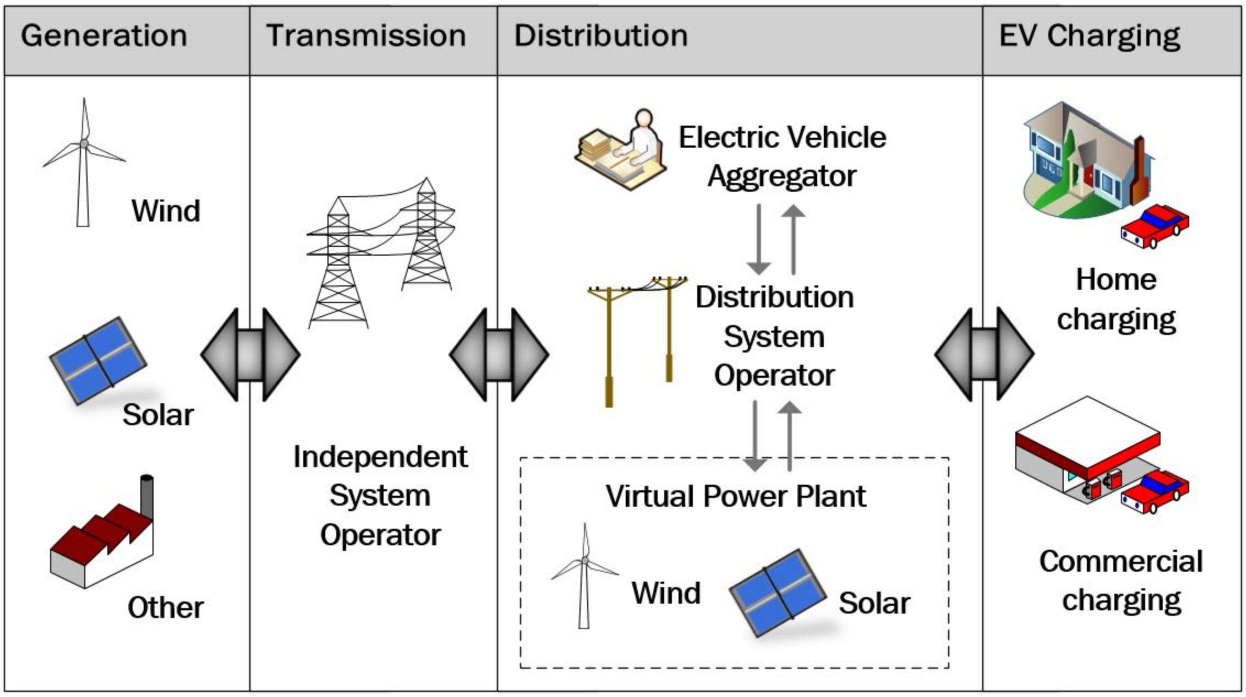


Figure 2.1: Supply chain of energy required for EV charging.

why EVs have not been successfully introduced in the market even though they may seem a better option.

Electric vehicles are more environmentally friendly than combustion engine vehicles. Nevertheless, they mat not be as green as we think. For example, taking into account that EVs are powered by the electricity and thus energy generation can come from different sources, the EV transportation as a whole is not necessarily emissions free. In addition, as the transition to renewable sources moves forward, uncertainty in energy increases and so increases the complexity of power systems [17]. Consequently, smart charging of electric vehicles is becoming increasingly important as it has the potential to adjust charging timings depending on different parameters of the grid.

Challenges embedded in the transition from combustion engine vehicles to electric vehicles are explored in this Thesis from smart EV charging perspectives. These perspective of research can be tackled in different research directions, one direction to this problem is related to the usage of Demand Side Management techniques which in fact are one of the most profitable ways to improve efficiency and utilities [18]. However, Demand Side Management approaches are widely used in different smart grid applications and it is important to define the elements in the Grid that are relevant to the EV system.

Several authors have studied the elements in the EV system. For instance, Shuai *et al.* [19] made an overview of different transactions of EVs and electric vehicle aggregators with a focus on economic goals of each agent and potential ancillary services. Similarly, Wang *et al.* [20] also explored these services and added more considerations regarding modeling uncertainties. An important consideration of the content of these two works is that they considered transactions between EVs and electric vehicle aggregators only. Other components of the network such as the grid and charging stations were not covered.

Moving on with other surveys, Rigas *et al.* [21] analyzes different EV charging strategies for grid to vehicle (unidirectional power flow) and vehicle to grid algorithms (bidirectional power flow). Richardson [22] on the other side, compiled several papers that assess impacts and feasibility of integration of wind and solar with the Grid to meet EV demand. We can see from both works that despite the importance of renewable sources of energy, the transactions of managing wind and solar generation in a charging station or a virtual power plant have not been deeply analyzed. The overview of Demand Side Management strategies in this Chapter, covers a new perspective of how to use demand response pricing schemes with different electric vehicle charging technology and EV user behavior. In addition, an overview of EVs integration with virtual power plants and energy hubs. These topics have not been fully covered in previous surveys.

More specifically, this Chapter presents the literature review of Demand Side Management fundamentals and applications in EV charging which introduces the big picture of the topics of research covered in Chapters 3-5. Section 2.2 introduces an overview of EV charging techniques as a background area to proceed to the analysis of Demand Side Management algorithms of charging stations in Section 2.3. Then, Section 2.4 provides an analysis how EVs can be integrated in operational transactions of a virtual power plant and be aggregated strategically in energy hubs.

Finally, Section 2.5 presents conclusions and future research challenges.

## 2.2 EV Charging Techniques

EV charging techniques can be classified in terms of the EV technology which can also be classified depending on charging speed, power flow, and electromagnetic fundamentals. For the purposes of studying flexibility of electric vehicles in this Chapter, EV charging techniques could also depend on the location of EV charging as EV driver behavior varies depending on where users charge. As this Thesis aims to study Demand Side Management tools for EV charging, charging techniques are analyzed from a flexibility perspective in this Chapter under the following classifications:

1. Static charging: this charging technique is used when a vehicle parked in a specific place [23]. It usually includes charging at home, work, car parks, etc. Thus, the flexibility for charging depends on EV users activities to do during a day while they shop, work and stay at home. EV charging duration last for minutes or hours depending on EV availability. The power transfer can be performed by conductive or wireless technologies at different charging speed, and with V2G (vehicle to grid) or G2V (grid to vehicle) capability.

2. Dynamic charging: it implies charging on the road or when a vehicle is moving. EV charging stations normally are located in specific areas on the road. EV charging duration happens in seconds, thus EV charging flexibility is limited. For this type of charging, there are too many challenges around maintenance and safety when using conductive charging technologies. Therefore, wireless power transfer charging technologies are popular in dynamic charging [24]. However, applications where conductive alternatives are widely used include railway applications [16].

We can see from the previous definitions that the two techniques also rely on the technology used. Cable charging topology consists of an ac/dc rectifier and a dc/dc

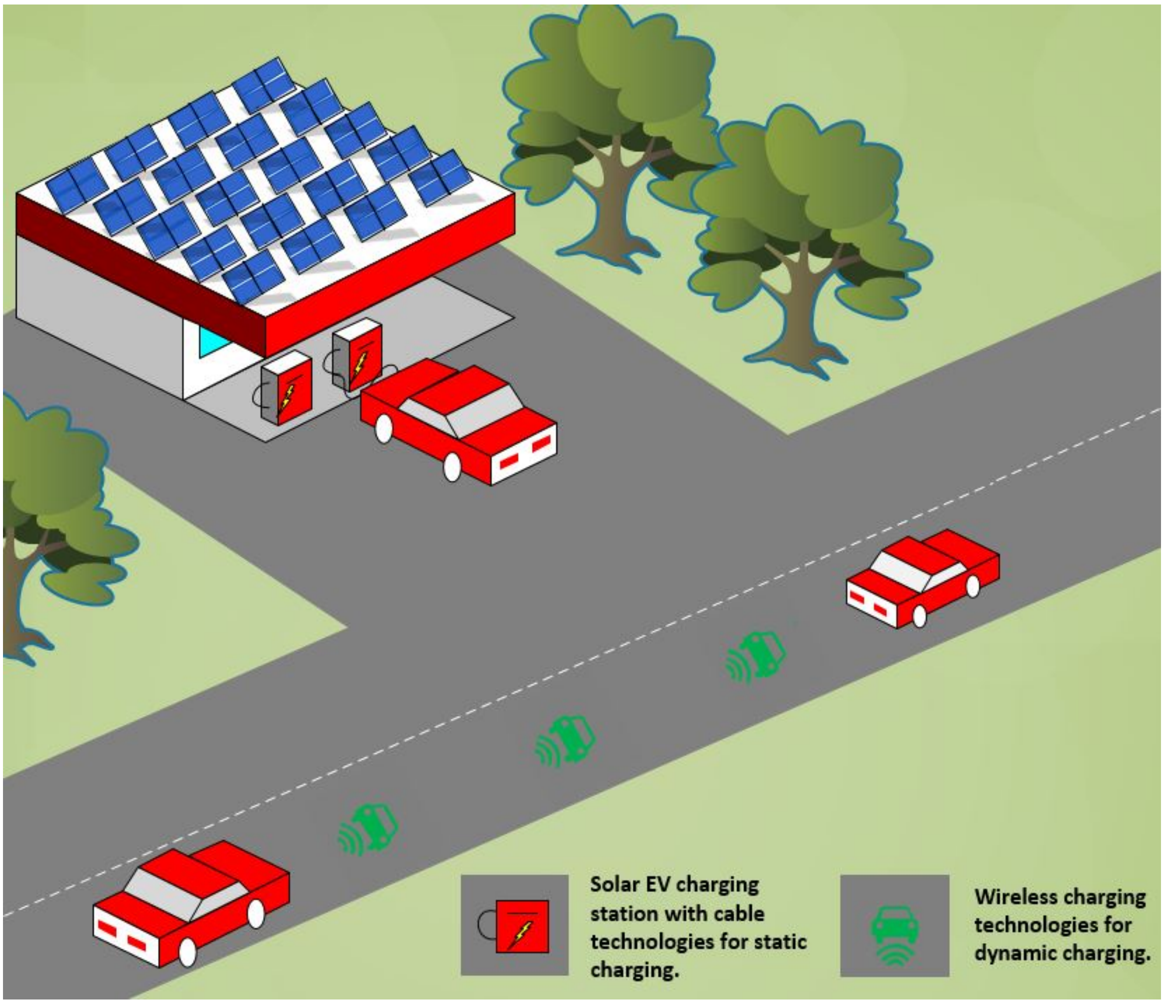


Figure 2.2: Example of EV charging techniques for charging at different locations and with different charging technology.

converter, another possibility is a low ac frequency source to a high frequency ac converter, both with a power factor correction [25]. Also, chargers can be on-board and off board, the difference is the location of the rectifier and current battery regulator which are inside the vehicle in the on-board option and are in the charging infrastructure for the off-board option [26; 27].

On the other hand, wireless transmission of electricity is cable free. Therefore, potential hazards like an electric shock due to their usage under weather conditions such as snow and wind, are diminished [23]. This infrastructure consists of a primary and a secondary coil, with coupling and pick up functions respectively, that transfer power through magnetic fields over an air gap [28]. An analysis in Great Britain suggests the range anxiety issue would be eliminated as EVs would charge while driving [29]. The main distinctive relative to the conductive option is that instead of having a transformer, the couple coils are used for the energy transfer [30]. As an illustrative support, Fig. 2.2 presents wireless and cable technologies inspired by EV charging stations in Norway [31] and an EV wireless charging assessment in the UK [29] .

The literature mainly discusses three categories of wireless charging: inductive power transfer, magnetic resonance and permanent coupling based [25; 32]. The first and second categories possess similar fundamentals of magnetic field induction, however the magnetic resonance is more efficient since the two electromagnetic components of the system share the same resonance frequency [33]. The last category uses a permanent magnet as one of the coils for electricity transmission [32].

The mentioned technologies in previous paragraphs can work for both the static and the dynamic case. However, the conductive power transfer may be reaching its limits for efficiency improvements compared to wireless power transfer technology. Wireless architectures on the road, could also help to reduce the battery size of vehicles [34] and to improve its life cycle [35], also they are considered a complimentary option to static charging [29]. Other potential benefits provided by this infrastructure are support for deployment of smart motorways (with automated charging and measurements of traffic flow data) and vehicle automation (with positioning in lanes no matter the weather conditions) [24].

Nevertheless, from EV Users perspective it is more common to describe EV charging techniques based on the charging speed as: slow charging (up to 3.6 kW) which is commonly used at residential areas and in lamp posts, fast charging (7-22 kW) commonly used in public charging locations and rapid charging (50 kW+), which is at the moment used in motorways and shopping centres [36; 37]. Users also need to check for the right plug connector as not all charging stations include all charging types and connectors. Consequently, as charging speed and plug connectors vary, the flexibility of EVs can vary depending on several factors such as charging location (depending on the charging speed infrastructure), EV arrival at the charging station and charging duration [38].

In addition, power flow for EV charging can happen unidirectional power transfer, when EVs can only be charged, and bidirectional power transfer where EVs can be charge and discharge energy to and from the grid. These two concepts are commonly known in the research community as G2V and V2G charging [39; 40]. V2G charging technology requires additional bidirectional converter compared to G2V technology [41]. Also, degradation and efficiency of charging is a concern in V2G technology [42]. However, bidirectional power flow could offer more flexibility support to the grid as EVs batteries could be used for a variety of balancing services and, as technology develops, degradation and efficiency may be soon become negligible.

To sum up, EV charging techniques were introduced in terms of static and dynamic charging, where EVs can be charged while EVs are parked or while EVs users are driving on the road. Then wireless and charging technology was presented, followed by charging speed ratings, and V2G and G2V technology. As this Thesis focuses on Demand Side Management tools applications in flexibility of EV batteries, case scenarios in the following Chapters are explored in static charging only at different charging locations (to consider driver behavior) and comparing V2G and G2V technology.

## 2.3 Demand Side Management

Demand Side Management is a promising tool for enabling the integration of renewable sources of energy [43] as it proposes the usage of different objectives for optimization of resources with application in the smart grids [44]. This becomes a critical consideration when modelling of environment dependable energy sources. For instance, research that use this tool proposes shifting energy loads from peak to off peak times, so that stakeholders and customers can cooperate to guarantee blackouts do not occur, where operational costs as well as electricity prices are minimized and $CO_2$ emissions are reduced [45]. Ideally, all parties or stakeholders involved would benefit from optimization of energy resources through the grid, the question is; what are the transactions and formulations that will ensure advantages for everyone and optimum use of charging resources?.

This section defines a classification of Demand Side Management models under different classifications. These are presented based on goals that include, costs, carbon emissions, customer satisfaction, etc. A further analysis is presented in terms of the control mechanism of the algorithm and differences between algorithms used in the static and dynamic framework. Then a deeper analysis of pricing or demand response mechanisms are explored. Finally, an overview of market structures for aggregation of EVs is presented.

### 2.3.1 Minimization of Costs and Other Objectives

Authors have modelled different algorithms for many intents and essentially, this defines the assets to obtain from the concept of Demand Side Management. Table 2.1 shows the classification of different papers based on the goals found, they can be clustered as follows:

- Cost Minimisation
- Revenue Maximisation
- EV Satisfaction Maximisation
- Peak Minimisation
- $CO_2$eq emissions Minimisation
- Fairness Maximisation

Let's start by looking at the straightforward goals. It is reasonable to think that models should include costs from customers, when buying electricity from either customers or the grid. In the same way, companies may look for a maximization of

Table 2.1: Summary of Literature Review of Demand Side Management Goals.

| **Table Ref.** | **Demand Side Management Goals** | | | | | |
|---|---|---|---|---|---|---|
| | Cost Min. | Revenue Max. | EV Satisfaction Max. | Peak Min. | $CO_2$ Min. | Fairness Max. |
| [46] | | ✓ | ✓ | | ✓ | |
| [47] | ✓ | ✓ | ✓ | | | |
| [48] | ✓ | | | ✓ | | |
| [49] | ✓ | | | ✓ | | |
| [50] | ✓ | | | ✓ | | |
| [51] | ✓ | | | | ✓ | |
| [52] | ✓ | | | | | |
| [53] | ✓ | | | | | |
| [54] | ✓ | | | ✓ | | |
| [55] | ✓ | | | | | |
| [56] | ✓ | | | | | |
| [57] | | | | ✓ | ✓ | |
| [58] | ✓ | | | | ✓ | |
| [59] | ✓ | | | | ✓ | |
| [60] | ✓ | ✓ | | | | |
| [61] | | | | | | ✓ |
| [62] | ✓ | | | | | |
| [63] | | | | | | ✓ |
| [64] | | ✓ | | | | |
| [65] | | | | | | ✓ |
| [66] | | | | | | ✓ |

profits, that is a percentage gain minus the offered price of electricity in the market. Yoon *et al.* [47] contemplates maximisation of profits and customer satisfaction for allocating energy for appliances and EVs at home charging location. On top of that, if there is a control of what sources of generation are utilized for electricity consumption, then a greener charging system could also help to reduce the $CO_2$eq emissions. Harry *et al.* [46] presents a regulator agent that can control a carbon factor to command the electricity charging rate for EVs depending on limiting factor values. A similar concept is proposed in [51] where the minimization of costs considers a combination of generation and carbon tax costs.

Recent work in smart charging strategies has opened the possibility to incorporate different goals in the area of demand side management with renewable energy integration. Heron *et al.* [57] proposed a curtailment charging strategy of EVs in a residential IEEE bus system with wind energy connection, where power and voltage signals were used as triggers to control EVs as flexible loads to maintain voltage levels and maximum power constraints. The observed benefits of this control schemes were peak shaving effects and $CO_2$eq savings. Mou *et al.* [58] modelled a demand response pricing scheme that considers both energy utilization from wind energy in wireless power transfer charging infrastructure, and users' willingness to pay for charging. Zhang *et al.* [59] proposed an economic dispatch to minimise $CO_2$eq emissions costs and operational costs of wind energy, thermal generators and battery storage system. Vasirani *et al.* [60], formulated a coalition of a wind farm with EVs to bid into a day ahead market using EVs as storage, then penalties were estimated when taking into account deviations in a real time basis.

The minimization of energy peaks is an interesting topic as there are many ways to approach this goal. After analyzing the location scenarios where the algorithms are developed for, we can see that investigators look for establishing transactions to be used for charging at home, charging at parking lots and charging on the move while passing on a lane road. In other words, energy balance is performed in one local case in the electricity network. If we assume an energy balance is achieved by matching supply with demand, then the approach from [49] presents a solution. Here, the intention is that customers do not deviate from the forecast of demand (obtained by a company) by taking advantage of at home production of renewables, charging of discharging of both energy storage systems and EVs. Another method is including a factor of energy balance in the equation, this factor can be used to moderate average load peaks as in [48].

A system wise approach is presented in [53] where different charging locations are recognized. Even though these algorithms are used for finding the EV routing path in the first place, they can be effective when one charging station is congested, as a consequence this minimizes energy peaks in an infrastructure system environment. In [54], Rigas *et al.* uses price congestion signals as promoters for allocating different energy time slots in charging stations, this balance is created as it is inferred that EVs look for cheaper prices. In this research work, prices are the main motivators for orchestrating an equilibrium. This leads us to our next subject in our literature review, the use of price schemes under the area of Demand Response.The reason to describe this topic in a separate manner is because unlike automated mechanisms, price balancing is customer dependant and therefore it is worth a deeper analysis. Thus, pricing is introduced in the next Subsection but before going to the next topic, let's finish this Chapter with another goal in Demand Side Management optimisation strategies.

The last objective in the list is related with the inclusion of different objectives and fairness in a problem formulation of EV smart charging schemes. Fairness can be addressed in different ways, for instance by modelling fairness driven heuristics or by selecting an optimal solution in multi-objective formulations. Carvalho *et al.* [61] proposed a fairness allocation and max-flow optimisation for charging of EVs at the distribution level. Wei *et al.* [62] proposed a nash equilibrum formulation considering user preferences of charging with renewable energy and cost savings. Ucer *et al.* [63] proposed a fair algorithm using a compliant additive increase multiplicative decrease TCP protocol to allocate power to EVs considering voltage limits and appropriate current changes at different feeders depending on distance to the transformer. Cui *et al.* [64] proposed a fair game between EVs and EV aggregator using nash equilibrium prices and taking into account uncertainty in regulation signals. In terms of multi-objective formulations in smart grids, fairness has been ensured using a pareto frontier with genetic algorithms as in [65; 66] and sorting heuristics as in [67]. However, research opportunities for ensuring fairness in EV charging along with reduction of carbon emissions are still present, and they represent a great chance to support decarbonisation in transportation and power systems.

### 2.3.2 Pricing for EV charging

Demand Side Management concept proposed that customers and charging operators can both have benefits from pricing programs [55]. Users can can take advantage of the pricing schemes offered while charging operators can use flexibility of users to change patterns in consumption as required by the grid [68].These programs can be traditionally classified as incentive and price based, where either energy savings or high/low prices respectively are offered based on different criteria [69].

Recent innovation projects have proposed to use the flexibility of EV charging for participating in energy markets to provide value from EV batteries to the grid. Vehicle to grid (V2G) technology allows EVs to discharge electricity back to the power grid given the bidirectional power flow capability. The report in [70] explored projects with V2G technology and noted that only one project is currently at commercialisation stage. This project of V2G fleet management was achieved by collaborative work of charging station producer Enel X, V2G vehicle companies Nissan, Mitsubishi and PSA Groupe, and an anergy aggregator company Nuvve [71]. Other projects are still in demonstration phase and aim to test for the feasibility of V2G support to the network, such as the new Electric Nation V2G trial in Wales, UK [72]. Thus, the integration of EVs with the power grid still presents research gaps where improvements can be done. One example of improvements is in the research area of the demand response of EVs, where smart charging strategies could be used to support financially sustainable operations of charging stations.

Electric vehicle aggregator publications of EV charging have concentrated efforts in the price based option where prices are announced in a day ahead and/or real time basis. Tushar *et al.* [49] proposes a model for the static charging scenario where EVs are integrated in the grid by using at home facilities. He states a two-phase communication model where users send a demand profile to the operator in the first phase (a day ahead), this helps accommodate electricity purchase for the next day. Then the operator updates electricity price in real time based on demand deviations or penalties. As a result, clients are price based encouraged to update their energy requirements.

In order to influence customers according to grid requirements, demand response programs have been used as promising tools to enhance penetration of more renewable energy sources in the grid, while encouraging certain patterns in customer energy demand [73]. Following forecasting of market clearing price and ancillary service prices, Chandra Mouli *et al.* [74] proposed aggregation of EVs parked in buildings integrated with solar panels to maximise the charging operator revenues. Lui *et al.* [75] proposed a dynamic pricing model for an EV aggregator using a reinforcement learning algorithm that considers updates from a spot market, price elasticity from users to compute energy prices and EV load changes. Tawfiq Masad *et al.* [76] proposed a real time pricing scheme using inverse demand curve to account for price changes when microgrids are congested. Chen *et al.* [77] proposed pricing schemes using cooperative and non-cooperative game formulations in order to achieve market equilibria. These works adequately considered how EV schedules can be adapted to pricing signals set by the charging station operator, however they assumed balancing prices are established by a grid operator. Thus, prices for auction markets has not been explored and pricing to influence driver behavior charging response to price changes was not carefully considered.

As described before, there are critical research gaps in pricing schemes for balancing services offered by EV charging. In addition, financial modelling represents one of the biggest barriers to commercialisation [70] and specially in the the case of V2G charging technology, where research to improve the utilities of charging stations is a critical topic that needs solving. Therefore, one of they key research directions for EV charging pricing schemes is about how to ensure customer responsive pricing scheme for the specific case of a commercial charging station with onsite solar generation participating in auction bidding markets.

### 2.3.3 Electric Vehicle Aggregator

The increasing number of EVs is widely seen as an opportunity to aggregate energy loads and support grid operations [78]. The energy vehicle aggregator could play an important role when establishing key communication packages between EV users and the distribution system operator, based on market opportunities and different goals from the agents involved. Table 2.2 shows a summary of market structures and energy balance strategies of energy aggregators or charging operators. Sortomme and El-Sharkawi [79] for instance, modeled EV bidirectional energy flow (charging and discharging) while providing frequency regulation and spinning reserves services to the Grid. Here, the frequency regulation is based on a preferred operation point. Another example of these ancillary services is proposed by de Weerdt *et al.* [80]. Their bidding strategy, however, only works when the price is lower than the market capacity clearing price, therefore it creates restriction to get revenues.

Many authors do not specify any particular ancillary service and refer to bidding strategies for the day ahead and real time market instead. Vardanyan *et al.* [85] precisely showed this type of strategy and their contribution focuses on stochastic methods to predict day ahead and real time energy prices as well as driving patterns. These methods are performed with Markov based on Holt Winter (seasonal nature) and Monte Carlo simulations respectively. Vagropoulos *et al.* [89] proposed a

Table 2.2: Summary of Energy Aggregators (EAs) Activities and Market Transactions.

| | | |
|---|---|---|
| **EV Aggregator** | Market structure | Day ahead and/or real time transactions [79; 80; 81; 82; 83; 84; 85] |
| | | Hierarchical transactions [86; 87; 88] |
| | Energy balance agents | G2V/G2G services [79; 80; 81; 82; 83; 84; 85; 87; 88] |
| | | Energy balance among EAs [82; 86] |
| | | Renewable units [83; 84] |

similar approach where the electric vehicle aggregator announces the energy bids to the market, then customers send their response information. After this, the electric vehicle aggregator updates in real time the new energy bids based on the actual energy consumption of users and offers new bids if necessary. In consequence, customers are penalized of any bid deviations. A further analysis is performed in [88] that integrates real time charging management transactions based on a preferred operation point. Then, the complete electric vehicle aggregator model is then integrated in a theoretical platform which can be consulted in [90].

In comparison to the day ahead, real time transactions and reservation programs mentioned previously, Lu *et al.* [86] proposed a hierarchical method to model interactions between distribution system operator with multiple energy aggregators. Here the model is formulated in two levels where the distribution system operator is the main leader of the game and the energy aggregators adjust accordingly. Junhao Lin *et al.* [87] proposes a similar hierarchical approach where EVs react to regulation signals under the aggregator-EV protocol.

Selected research in the area show advances in energy bidding and pricing depending on market designs and the business models of the charging station operator. Sortomme *et al.* [91] designed a bidding mechanism to model all possible V2G capability for frequency regulation and spinning reserves to maximise charging operator revenues. Nakano *et al.* [92] proposed aggregation of EVs and plug-in hybrid vehicles using a home energy management system for residential households to participate in a regulation market with different time scale control mechanisms. In addition to research works of EV energy management support at the transmission level, such as the ones previously described, Mizuta *et al.* [93] proposed a model for balancing services at the distribution level to mitigate voltage imbalance using ordinary differential equations to represent distribution voltage. Data uncertainties when aggregating EVs for balancing services have also been considered using bias measurements of regulation signals as proposed by Cui *et al.* [64], and pricing regulation predictions using seasonal auto regressive integral moving average model as proposed by Cai and Matsuhashi Cui [94]. These research works have provided contributions in terms of control for energy bidding of EVs parked in residential locations and uncertainties in the system, however pricing mechanisms to engage customers to participate in balancing services were not considered, and stochastic behavior and demand response nature of EVs were not explored.

Regarding exchange of packets of information to support communication between electric vehicle aggregators operations, Gupta *et al.*[82] used an entirely reservation scheme to model day ahead and real time transactions. The day ahead transactions are focused on charging reservations of EV drivers for the next day. Then based on real time EV driving updates, reservations can be cancelled or traded with different energy aggregators that own and communicate to their owned charging stations. Drivers are penalized in case of cancellations and energy aggregators have transaction charges between them. Cao *et al.* [88] made a deeper study of a real time reservation program for EV mobility. EVs can send en-route updates of reservations to increase accuracy of the electric vehicle aggregator in terms of waiting time at stations.

In addition to buy electricity from distribution system operators, electric vehicle aggregators could also collaborate with other agents to get profits. Lu *et al.* [86]

showed the possibility to consider an alternative balancing energy measures by trading with different energy aggregators. A remarkable point is that the aggregators are able to rent storage space (in case of excess of energy) or buy energy bid from each other. This system works under the assumption that the distribution system operator manages these transactions and coordinates energy bids. The distribution system operator's goal is to minimize costs while maintaining network constraints. The aggregators then have the authority to prioritize bid offers and look for the cheapest option until power demand is covered. Then each energy aggregator offers energy bids to the higher price taker. In contrast with this method, Wu *et al.* [83] presented a nash equilibrium bidding strategy to balance bidding strategies of electric vehicle aggregators.

Another energy trading method is proposed by Gonzalez and Andersson [84]. The proposed method integrated wind generation and G2V/V2G (vehicle to grid and grid to vehicle) services. For this, the authors used a chance constraint based on different scenarios to address the uncertainty of driving patterns and energy deviations. Another model is also proposed by Wu *et al.* [83] as a unit commitment strategy to control operations of wind and emergency turbines. Regarding some other important aims and restrictions of electric vehicle aggregator models, de Weerdt *et al.* [80] penalized the cost of EV battery degradation in the main objective function. Electric vehicle aggregation restrictions are charging and discharging limits as well as their respective rates per battery constraints. Charging and discharging is performed while ensuring that the state of charge at departure reaches a minimum stage with a risk to fulfill customers' final state of charge specifications. This is different to the final state of charge restriction in [87] where the authors propose EVs to have enough energy until the next energy provision.

## 2.4 EV Charging System Integration

After exploring EV charging techniques from perspectives of flexibility related to EV behavior, and charging technology; aggregation techniques in energy markets were introduced in research that considered a third entity that managed EV charging schedules known as an electric vehicle charging aggregator that mediates flexibility services with the grid operators. This section continues with overview of EVs in combination with energy storage, renewable sources of energy, in other words, EVs are integrated as a virtual power plant. To finish with the literature of Thesis, energy hub research is explored to provide an introduction of the importance of aggregating EVs in specific locations with certain sizing of charging stations.

### 2.4.1 EVs and Virtual Power Plants

The increasing uncertainties in renewable generation and demand (EVs) of electricity have also been modeled in combination with Virtual Power Plant environments. The concept of a virtual power plant lies on the supply side element of the electricity grid. It acts as an entity to aggregate different sources of generation which can be renewables and non renewables, to maintain reliability of energy generation Energy Storage Systems (ESS) such as battery energy storage, hydraulic energy storage, etc. are used to meet energy loads [103; 104]. It is generally classified in the Commercial Virtual Power Plant (CVPP) and the Technical Virtual Power Plant (TVPP) [105]. However both concepts complement each other. For instance, Danish EDISON Project contemplates a two operational layered environment, the first is made out of the electrical infrastructure and the second is the commodity that interacts with the market [106]. Both classifications as well as the models and elements of different virtual power plants will be discussed below in order to analyze strategies to include EVs in smart grids.

Load aggregation is a key element in a virtual power plant (aggregation in different layers) that could help trigger demand response programs when required. Digitalisa-

Table 2.3: Summary of Virtual Power Plant Formulations

| Ref. | Goal | Constraints |
|---|---|---|
| [95] | MAX= Utilities (energy bids, spinning reserve and reactive markets) - Costs (generation, storage, curtailable load, capacitor bank, power factor penalty) | Ramp up and ramp down, start up and shutdown and capacity limits. Actions of active and reactive load curtailment. Energy Storage Systems (ESS) limits and charge/discharge actions. Capacity Bank (CB) steps (start up and shutdown) |
| [60] | MAX= Revenues (aquired from energy supplied to the grid from both the wind farm and EV batteries) - Energy imbalance costs | Energy balance, EV storage capacity limits, EV battery SOC restrictions and operations. |
| [96] | MAX= Profits from sold energy-operational costs of TVPP (distributed generation, market energy purchase, energy supplied to EV's, customer incentive penalty) | Active and reactive power balance and power flow through the lines, operational limits at each bus, EV battery charge and discharge, restrictions of SOC (EV battery) |
| [97] | MAX= Utilities from energy trade - Costs (energy generation, carbon trading and charge/discharge of EVs) | Carbon emission mechanism, uncertainties in demand, dynamics of SOC of EVs, gas turbine's restrictions (power output and ramp-up/down limits, power balance of the overall network |
| [98] | MIN= Generation costs + carbon emissions (policy maker) + bill payment from customers | Power limits of distributed generation and EVs, power balance, power output and ramp-up/down constraint. |
| [99] | MIN= Costs (total current*voltage*power factor*energy price per hour) | Algorithm conditions can be: weather, storage, price, signal and grid status conditions. |
| [100] | MIN= Costs (from power exchange and power imbalance penalties) | Wind power limit (predefined), supply and generation balance. |
| [101] | MAX= Supply Reliability, MIN= Number of interactive entities . | Energy price, expected and real energy production (which is determined by weather). |
| [102] | Specific active and reactive power requirements from distributed generation units and the grid. | Voltage regulation parameters, power at substations. |

tion of accurate information systems and control through all decentralized systems are also key factors to consider in order to have an efficient virtual power plant [107]. To begin with the overview of virtual power plants, let's start by looking at the commercial side of a virtual power plant. Nezamabadi *et al.* [95] proposed a spinning reserve service to the grid (frequency control) and a reactive power service. Having this in mind, they model an arbitrage strategy to take advantage of change of prices and operational functions of the virtual power plant such as recharging batteries when prices are low and sell energy to consumers when required. Another example is load curtailment, as it happens when demand of energy (supply) is more needed. Their work show a significant increase of profits when establishing virtual power plant operations following arbitrage opportunities. However, the authors do not model a dynamic operational model of the virtual power plant and do not consider other costs such as project investment.

Another study that explores the commercial side of a power plant was proposed by Zhao *et al.*[100]. In this paper, a search method is used to find the optimal solution that could reduce costs, which are modeled as a expected function of power limit of a wind turbine (used for curtailment of energy), the bidding strategy and price uncertainty. The algorithm finds the optimum wind upper power limit that has the most profitable bidding strategy. However the foundation of the model assumes that the load (demand) follows a normal distribution, in other words, this model may not be accurate for a demand which is for example non parametric.

Aggregation of entities in the virtual power plant therefore requires a careful analysis about how to integrate all agents in a fair and profitable way. Chalkiadakis *et al.* [101] shows a good example of a coalition of different wind units who are aggregated by an agent. This paper proposed prices to control payments to the wind units which are mainly based on supply reliability. Then, there is a scoring process to eliminate or maintain the different wind units. These units are either expelled or rewarded for their supply. This research however fails to include other specific functions of a virtual power plant such as energy management and demand response programs.

Other advantages of a virtual power plant rely on its flexibility nature which can provide environmental and economic benefits. Liu *et al.* [97] proposes a model that considers carbon trading mechanisms in a market where it is assumed that carbon penalties are charged to virtual power plant operators. Here, carbon credits, which are assigned to each virtual power plant and are controlled by a monitoring system, can be traded between different virtual power plant to maintain an overall carbon limit. In contrast, Hua *et al.* [98] uses a carbon weight factor (policy maker goal) in the objective function of the virtual power plant's modus operandi to control carbon emissions. Moving on to a more technical functional part of a virtual power plant, Abdolrasol *et al.* [99] proposed the design of a controller which can swtich on/off each microgrid in the virtual power plant to control and optimize power flows. Similarly, Dall'Anese *et al.* [102] proposed a control model where different power output controllers are monitored to minimized specific operational goals of the distributed generation units and an agent (transmission system operator).

Most of the virtual power plant designs considered that the infrastructure to flexible loads can be integrated with elements such as renewable energy, distributed energy, energy storage systems and IL switches. Another consideration of other elements of the virtual power plant is the type of energy storage systems contemplated, for instance, EV batteries are modeled as an extension of a windfarm to provide energy services to the grid. The EV users could be rewarded with payments in terms of energy for letting charge and discharge their batteries through time. Recent studies have included customers satisfaction and specially when modeling a demand response program. This is because customers may not be satisfied with prices or curtailment of electricity. An example of customer satisfaction modelling was proposed by Hua *et al.* [98] where customers dissatisfaction increases quadraticaly with the power used in a demand response program. This dissatisfaction level is also directly proportional to an inelastic customer parameter.

### 2.4.2 EV Charging Hub

Key aspects of EVs have been introduced in order to provide an overview of demand side management tools that can be used in EV charging, and the flexibility potential they can offer in different energy markets. EVs integration with smart grids in the form of a virtual power plant as also been introduced, where it was important to consider optimised usage of energy resources for different goals. Having mentioned the potentials of smart charging schemes for EVs, charging operators and grid operators, this subsections finalises the literature review of this thesis with an overview of formulations used for the design of EV charging hubs that include sizing and/or location.

Xie *et al.* [116] proposed a simple model to determine the minimum number of charging stations in highways based on the recharging places required for EVs. The charging places are estimated with a monte carlo simulation of both stochastic battery capacity and stochastic state of charge. The authors assume that that EVs maintain a constant speed and that there are no losses/gains in energy while driving in a highway (for example during regenerative breaking). Some of the drawbacks of this model is that there are no constraints regarding costs, also recharging points could be too close to each other.

Dominguez-Navarro *et al.* [117] proposed an optimization model to determine the ideal design components of a fast charging station such as: number and rated power of the chargers, power of renewable generators, power and energy of the batteries, contracted power in the grid connection point needed to feed the charging station. This is very interesting as the models consider not only the technical operations of the grid but also the revenues to obtained depending on the initial investment and operational costs according to the previously mentioned design variables. The results (based on electricity prices of Spain) showed that the usage of renewable sources of energy and battery storage options in the charging station significantly reduce the impact of power required from the grid. Besides, it is more profitable to install storage systems and renewables than just buy electricity from the Grid.

A discrete markov chain model was proposed by Ugirumurera *et al.* [115] to determine the number of solar panels and the size of an energy storage system considering the following factors in a steady state probability: departure/arrival of EVs, radiation

Table 2.4: EV Energy Hub design

| Ref. | Goal | Constraints |
|---|---|---|
| [108] | MIN = Costs (investment, customer's power outage, power losses and voltage deviations, pollutant emissions). | Limits of line flow, bus voltage, capacity of station and energy generation, power flow operation. |
| [109] | MAX = Discharging and charging services, grid services, power losses, reliability, -investments. | Power flow, voltage limits, thermal limits of feeders or substation, charging station capacity, demand response program limits. |
| [110] | MIN = Costs (investment, land rental, connection, energy losses, demand response program). | Power capacity of connector and charging station, voltage profile, transmission line flow. |
| [111] | MIN = Costs (Investment and Operational). | EV demand (drive range requirements), quality of service (quantity of required stations), PV operation and limits, power network operation (power flow, voltage limit, buying and selling of electricity). |
| [112] | First stage (Deterministic): MIN = Costs (Investment and Operational), Second Stage (Stochastic): MAX MIN = Slack variables of voltage rise and drop, worst case power flow. | First stage: active power flow, reactive power flow,voltage based in supply and demand. Second stage: feasibility electric vehicle aggregator based on uncertainties of the system. |
| [113] | MAX = Revenues. | Power balance, power fluctuation limits, ESS and battery converter operations. |
| [114] | MIN = Power losses, MAX = number of generation units, charging station and ESS. | Power flow and power balance, voltage limits, uncertainties of solar and wind energy generation, charge and discharge limits of ESS. |
| [115] | MIN = Costs (investment and operational). | Limits of waiting time of EVs at a charging station, time dynamics. |
| [116] | MIN = Number of charging stations and investment costs. | Demand requirements (SOC and travel range), charge and discharge of ESS, limits of ESS and the correspondent power losses, uncertainty of generation and supply, failure of power supply. |
| [117] | MAX = Revenues. | Cost functions, energy balance, power limits (energy generation,charge and discharge of ESS, connection point, energy supplied to EV and charging supplier) , maximum customer waiting time. |

levels, storage systems's state of charge. Therefore, it is assumed that certain information is known such as EV arrival rates, energy demand requirements, number of charging stations in the system and power capacity, technology used etc. The aim of the design is to minimize investment and operational costs taking into account a maximum waiting time for each EV. Interestingly, the authors design the charging station with a supply priority policy, where solar energy is used as a first resource followed by the usage of energy in energy storage systems.

Arias *et al.* [118] proposed a model of electric vehicle aggregator in a distribution system operator network expansion project that considers the minimization of the overall net present value in different cases and construction stages. Hence, the goal is to minimize all associated costs; circuits, substations, capacitor banks and distributed generation units while satisfying system limitations associated to Kirchhoff's laws. A chance capacity constraint is implemented to estimate uncertainties in load and EV demand. In similar way, Pazouki *et al.* [119] proposed a model to place a charging station as a grid expansion. The Grid considerations in the problem formulation are: line flow thermal limits, bus voltage limits, capacitor and CS limit and line power flow.

Xiong *et al.* [120] presents a different approach where the allocation model minimizes the overall charging costs in terms of travel and queuing time in a region. Y.S. Lam *et al.* [121] explores a graph theory formulation where the aim is to minimize the construction cost in different locations based on traffic conditions in different areas. This model however assumes a previous distribution system operator analysis is made with potential location points, these are therefore inputs of the final step selection process. Zhao *et al.* [122] studied a two-stage optimisation technique to electric vehicle aggregator to evaluate financial and grid related concerns. The model first evaluated the minimization of investment of costs including installation and lifetime of solar panels and wind units. All of this is subject to grid constraints as well as average forecast for renewable generation and monte carlo simulations used to estimate EV traffic demand. Then a second stage is used to analyse the feasibility of the charging points to meet specific security network in a worst-case power flow scenario which is relaxed by some slack variables of voltage rise/drop and network line capacity.

## 2.5 Chapter Remarks

### 2.5.1 Research Challenges

The literature review in the previous sections highlighted research opportunities in the topics of Demand Side Management where pricing, EV aggregation and optimisation of EV charging with different goals play an important role in smart EV integration with the grid. In addition, the integration of EVs modelled as virtual power plants and as EV charging hubs was also introduced. There are five main research gaps that were found in the literature, these are addressed as objectives of this thesis as described in Table 2.5. The first research gap is related to more pricing strategies that could influence in EV charging behavior changes to use EVs as flexible loads. The second research gap is related to limited research that considers EV integration including stochastic nature of EV charging behavior and EV user engagement when participating in balancing services. The third research gap is related to limited modelling of EV charging scheduling that considers not only revenue and cost maximisation but also reduction of carbon emissions while ensuring fairness of all goals. The fourth research gap is related to limited research that considers evaluation of EV flexibility in varied locations with different charging ratings. In addition to these four research gaps, it was found that there is very limited assessments on performance of a charging station operation, thus this is added as a research gap also inherent to assessing the EV charging modelling proposed in this thesis. These research gaps are discussed in the following five paragraphs with more detailed explanations.

Real time and day ahead programs are widely used as price programs in models

Table 2.5: Summary of research gaps, thesis objectives and contributions.

| Research gap | Objective | Contribution |
|---|---|---|
| -Pricing strategies that could influence in EV charging behavior changes to use EVs as flexible loads.<br>-Stochastic nature of EV charging behavior and EV user engagement when participating in balancing services.<br>-Evaluation of EV flexibility with different charging ratings. | -***Objective 1:*** to design a pricing scheme that can influence EV drivers to participate in balancing services.<br>-***Objective 2:*** to design an EV charging control planning scheme to account for bidding and EV charging. | -New dynamic time of use pricing scheme based on inverse demand curve that ensures users engaging behavior, demand responsive pricing scheme solves pricing dilemma of charging operator prices.<br>-Bi-level optimisation with pricing and EV charging optimisations capable of modelling stochastic EV charging behaviour and different charging technologies for balancing services integration. |
| -EV charging scheduling that considers not only revenue and cost maximisation but also reduction of carbon emissions while ensuring fairness of all goals.<br>-Evaluation of EV flexibility in varied locations with different charging ratings. | -***Objective 3:*** to design a control scheme for EV charging to reduce carbon emissions.<br>-***Objective 4:*** to design a multi-objective optimisation approach to ensure fairness between all objectives and evaluate the trade-offs. | -New formulation of smart EV charging to reduce carbon emissions that includes goal of EV users, charging operator and carbon regulator.<br>-New modelling integration with genetic algorithm to ensure fairness and reduction of carbon emissions. Two non-dominated criteria is proposed: best ranked solution and minimisation of carbon emissions. |
| Assessment on performance of a charging station operation. | -***Objective 5:*** to analyze what parameters can improve the performance of a charging station. | -Strategic assessment, made with sensitivity analysis using one factor at a time method, to evaluate selected parameter inputs measured by performance indicators. |

used for EV charging as shown in the previous section. The real time price based program by itself however, has many challenges such as volatility in prices [123] and active requirements for participation of customers [43] which may not be very attractive for the users [124]. These price schemes can serve as the main motivators for influencing change in demand and a deep analysis is encouraged to maintain a fair resolution of interests between companies and customers [125]. Note that these are not the only demand response programs available and there is opportunity to incorporate different schemes like ancillary services, for more information [44] and [69] can work as a guide for programs used in smart grids.

The rapid transition from combustion engine vehicles for EVs translates in different challenges but also opportunities as EVs can be used as mobile virtual plant energy storage untis for supporting the grid when necessary. EVs could also benefit from selling back energy to the grid and other programs related to integrated parking and charging facilities. Transportation services that own EV fleets could also liaise with energy aggregators and distribution system operators to have a mutual advantage on charging services, grid reliability and revenues. Some key consideration from the best practices modeling techniques in the research analyzed include consideration of stochastic nature modeling for nonrenewable sources of energy, market trading mechanisms in order to incorporate demand programs that could balance the grid, reduce carbon emissions and integrate renewable sources of energy. Diversification of balancing or ancillary services and EV users engagement could be critical for the maximisation of flexibility services with EV batteries.

Most of the Demand Side Management models analyzed, concentrated their efforts in achieving revenue and costs benefits. Some authors also considered inputs from consumers in terms of their satisfaction that can impact for example price or charging rates. Currently, there is limited research that considers reduction of $CO_2$ emissions based on price or a carbon factor. An interesting observation here is that so far, not many models have managed to include all goals in a same case, therefore there is opportunity to integrate for instance the costs or revenues, customer satisfaction and a variable of $CO_2$eq emissions. It would be interesting also to fairly control EV charging and create new business models to promote public engagement and transparency of information of energy renewable generation.

Renewable sources of energy are still a challenge in terms of power certainty provision. A successful implementation could consider the limitations of power for new distributed micro-grids and its corresponding inter-operability factors such as the use of energy storage systems all forms of charging scenarios (work, home, street, parking lot), control and energy management strategies when there are any voltage or frequency violations. Future study cases could also include interaction with other electricity consumption loads like heat pumps and any home appliances. Other potential scenarios to electric vehicle aggregator can be: wireless charging in renewable charging stations, semi isolated micro-grid models with wind and solar power provision where regulations allow this (home or street parking), models that include maximisation of use of local and zero carbon energy provision.

Additional points to consider when integrating EVs with the grid of this thesis are related to expansion of operations of the charging station operator and the hardware and software necessity to implement smart EV charging transactions. These points are our of scope of this thesis but are important aspects for the operation of the charging station operator. The first point is related to expanding operations worldwide is compliance adaptations to different electricity markets. The placement of EV charging stations should ensure an economical operation considering all investments, operations and maintenance requirements from different points of view: expanding current networks or placing different charging points in the current network. These methods should also consider any violations of network operations (transformers, capacitor banks, etc). Business operations can evaluate different cases where an external entity can operate a charging station or it is operated by the owner of the distribution network. In addition, when evaluating placement of new EV charging stations, evaluation of convenient locations such as current petrol charging stations can be a feasible option as they may be already placed in practical locations for EV users. Open research opportunities could include more interdisciplinary approaches that integrate knowledge and application of electricity markets, control mechanisms, software interfaces for grid monitoring and trading (energy markets and network operation control).

Finally, the second point is related to enablers of smart grid operations, the digitalisation and monitoring of the network that could play a critical role when establishing the transactions between the distribution system operators, energy aggregators and EVs to cope with reliability of the grid (voltage limits, frequency limits, etc.), customer satisfaction (EV driving requirements and fair pricing). Flexibility management strategies should make sense in a centralized and decentralized point of view of energy management strategies. Thus, new models can contemplate the integration of power electronics, software optimization systems and transactions with energy trading mechanisms. An existing innovation of these smart grid enablers can be found in [126].

### 2.5.2 Conclusions

The integration of EVs in the grid is a topic that has gotten research attention in recent years as different countries are aiming for a reduction of $CO_2$eq emissions in the transportation system. For this reason, there are research potentials for creating business models around EV charging programs using different charging technology. First, EV charging techniques were introduced to provide an insight into EV driver behavior at different locations, also capability of charging technology and its relation to flexibility of EV batteries. Then, a summary of Demand Side Management tools in optimisation of EV charging was presented to show the different goals in selected literature in the area. A deeper analysis of pricing and demand response programs was integrated also to provide an overview of the benefits and potentials of pricing to influence EV user behavior. Then, strategic integration of EVs with other energy resources was covered in an overview of virtual power plants. Finally, a quick introduction to the design of energy hubs to aggregate EV batteries was presented to also to highlight the importance of aggregation of EV charging in different locations with varying charging station sizing.

The management of energy in the grid draws many challenges to address. As a system network, the grid can interact with EVs by using different infrastructures and with variable smart charging transactions. To conclude, EVs represent a future extra energy load to the grid but also a virtual power plant of EV batteries that can be aggregated to provide support in grid services. To achieve an optimum integration with the complex electricity network, different approaches are required to control electricity transactions in different charging environments and driving routes of users. Important modelling considerations with research gaps in smart charging schemes include customer engagement (fair charging and pricing) and minimisation of $CO_2$eq emissions while participating in ancillary or balancing services. $CO_2$eq emissions could be reduced by considering a carbon factor while fair charging mechanisms could cover multi-objective optimisation approaches and dynamic real time pricing where users could shift charging and take advantage of cheap tariffs. An integral and smart charging system with these considerations is required in order to guarantee $CO_2$eq emissions are reduced and EV users are engaged with charging schemes. Research on charging schemes with these considerations could support the transition to a decarbonised transportation sector so that world political and environmental goals are achieved.

# Chapter 3

# Dynamic Pricing and Control for EV Charging

## 3.1 Introduction

As the transportation sector moves towards the replacement of the combustion engine with an electric one, the power sector also moves from high-carbon emission energy generation sources to low-carbon emission ones, such as wind, solar and biomass energy. However, this transition brings significant challenges to power systems reliability and resilience due to the increasing complexity of balancing energy demand and supply [127]. This increasing complexity could come from both intermittent renewable energy sources and increasing power demand, for instance as a result of more electric vehicles (EVs) [128]. Consequently, more frequent control requirements and reformed ancillary services provision is required to improve and maintain power networks [129; 130]. The development of EV charging technology and demand response programs bring an opportunity to aggregate EVs' power demand to participate in current and emerging energy markets, thus it could facilitate the transition to decarbonisation of the transportation sector [131; 132; 133]. Thus, the aim of this chapter is to propose a demand response model that considers planning mechanisms for the operation of a charging station operator that determines pricing and EV bidding estimation in order to participate in balancing services.

In specific, the model proposed in this chapter aims to tackle ***Objective 1*** and ***Objective 2*** which were stated in the Introduction section of this thesis. ***Objective 1*** is to design a pricing scheme that can influence EV drivers to participate in balancing services. The contributions related to this objective are: new dynamic time of use pricing scheme based on inverse demand curve that ensures economical and EV user engaging behavior, demand responsive pricing scheme solves pricing dilemma of prices for EV users and prices for participation in balancing services. ***Objective 2*** is to design an EV charging control planning scheme to account for bidding and EV charging. The contributions related to this objective are: bi-level optimisation with pricing that feeds into EV charging control optimisation that produces bidding and charging schedules, this EV charging control optimisation used for computing EV charging schedules is capable of modelling stochastic EV charging behavior and both V2G, bidirectional or vehicle to grid power flow, and G2V, unidirectional or grid to vehicle power flow technologies.

Recent innovation projects have proposed to use the flexibility of EV charging for participating in energy markets to provide value from EV batteries to the grid. Vehicle to grid (V2G) technology allows EVs to discharge electricity back to the power grid given the bidirectional power flow capability. The report in [70] explored projects with V2G technology and noted that only one project is currently at commercialisation stage. This project of V2G fleet management was achieved by collaborative work of charging station producer Enel X, V2G vehicle companies Nissan, Mitsubishi and PSA Groupe, and an anergy aggregator company Nuvve [71]. Other projects are still in demonstration phase and aim to test for the feasibility of V2G support to the network, such as the new Electric Nation V2G trial in Wales, UK [72]. Thus, the integration of EVs with the power grid still presents research gaps where improvements can be done. One example of improvements is in the research area of the demand response of EVs, where smart charging strategies could be used to support financially sustainable operations of charging stations.

Selected research in the area show advances in energy bidding and pricing depending on market designs and the business models of the charging station operator. Sortomme *et al.* [91] designed a bidding mechanism to model all possible V2G capability for frequency regulation and spinning reserves to maximise charging operator revenues. Nakano *et al.* [92] proposed aggregation of EVs and plug-in hibrid vehicles using a home energy management system for residential households to participate in a regulation market with different time scale control mechanisms. In addition to research works of EV energy management support at the transmission level such as the ones previously described, Mizuta *et al.* [93] proposed a model for balancing services at the distribution level to mitigate voltage imbalance using ordinary differential equations to represent distribution voltage. Data uncertainties when aggregating EVs for balancing services have also been considered using bias measurements of regulation signals as proposed by Cui *et al.* [64] and pricing regulation predictions using seasonal auto regressive integral moving average model as proposed by Cai and Matsuhashi Cui [94]. These research works have provided contributions in terms of control for energy bidding of EVs parked in residential locations and uncertainties in the system, however pricing mechanisms to engage customers to participate in balancing services was not considered and stochastic behavior and demand response nature of EVs was not explored.

In order to influence customers according to grid requirements, demand response programs have been used as promising tools to enhance penetration of more renewable energy sources in the grid, while encouraging certain patterns in customer energy demand [69; 73]. Following forecasting of market clearing price and ancillary service prices, Chandra Mouli *et al.* [74] proposed aggregation of EVs parked in buildings integrated with solar panels to maximise the charging operator revenues. Lui *et al.* [75] proposed a dynamic pricing model for an EV aggregator using a reinforcement learning algorithm that considers updates from a spot market, price elasticity from users to compute energy prices and EV load changes. Tawfiq Masad *et al.* [76] proposed a real time pricing scheme using inverse demand curve to account for price changes when microgrids are congested. Chen *et al.* [77] proposed pricing schemes using cooperative and non-cooperative game formulations in order to achieve market equilibria. These works adequately considered how EV schedules can be adapted to pricing signals set by the charging station operator, however they assumed balancing prices are established by a grid operator. Thus, prices for auction markets has not been explored and pricing to influence driver behavior charging response to price changes was not carefully considered.

As described before, there are critical research gaps in pricing schemes for balancing services offered by EV charging. In addition, financial modelling represents one of the biggest barriers to commercialisation [70] and specially in the the case of V2G charging technology, where research to improve the utilities of charging stations is a critical topic that needs solving. Therefore, this chapter proposes a dynamic, customer responsive pricing scheme for the specific case of a commercial charging station with onsite solar generation participating in auction bidding markets. Specific contributions of this chapter are outlined below:

1. Novel dynamic pricing scheme creates a tariff that changes using grid analytics (historical charging behavior) from customers responses to price and maximisation of revenues from the charging station, considering onsite solar generation and profitable financial relationships of an inverse demand curve which are prices and EV charging rate. This type of tariff provides an economical and customer engaging solution that solves the pricing dilemma of energy and price setting when estimating pricing for EV charging, and profitable incentives to increase or decrease charging rate, and auction bidding prices for participating in balancing services. To the best knowledge of the author of this thesis, this type of pricing scheme which can be used in auction based markets, where charging operators send price and energy bidding information to grid operators, has not been explored in previous research.

2. A bi-level optimisation approach is proposed where the pricing is the first

optimisation module that is used for setting pricing from the perspective of a charging station operator that aims to have additional revenue streams to EV charging when participating in balancing services. Then the EV charging module is the second optimisation that estimates an optimal charging rate from EV users perspective, following pricing signals from the charging operator while meeting customer and charging technology restrictions. These two optimisations simulate an economic and demand responsive behavior of both the charging operator and EV users respectively.

3. The bi-level optimisation is modelled using a new stochastic EV charging planning bidding optimisation that manages unidirectional grid to vehicle (G2V) and and bidirectional vehicle to grid (V2G) charging technologies to provide a perspective of potential revenue streams as well as energy bidding capability to support with balancing services. This EV charging aggregation bidding control is able to handle probabilistic arrivals, departures, trip requirements, EV user availability, battery size restrictions and varying charging rates.

The remaining parts of this chapter are organised as follows. The proposed model is introduced in section 3.2, where the time of use dynamic pricing optimisation and EV charging control optimisation are presented. Simulation settings and the merits of the proposed model are evaluated in section 3.3. Finally, discussions and conclusions are presented in section 3.4.

## 3.2 Problem Formulation

The model presented in this chapter consists of an EV aggregator or charging operator of a group of EVs with connection to the transmission or distribution system operator. Figure 3.1 summarizes the activities and exchange of messages for the operation of the charging station participating in balancing services when using EVs as flexible loads. The EV aggregator could be the owner of the charging station that is capable of buying electricity from the grid, of producing onsite solar generation, of selling/buying electricity to EV users and of selling energy to the grid for balancing services provision. With the use of Information and Communication Technologies (ICT), the EV aggregator can know in advance important information for the charging station operation such as EV drivers response to price, arrivals, departures, trip requirements and solar power forecast. This information is used as a data driven approach for estimation of price strategies that maximise revenues based on historical customer response to price during a day. The data driven approach consists of regression of historical price and hourly EV charging behavior from EV users and estimates of cost of energy including onsite solar generation, that is used for creation of optimisation of demand responsive pricing strategies. Then, historical arrival, departures, and trip requirements are used for optimisation of EV charging scheduling. Given the price optimisation, energy bidding coming from EVs is estimated using a control optimisation that evaluates demand response of EV drivers. Finally, the potential revenues from V2G and G2V charging technology are presented to comprehend EV driver response to prices given a predetermined dynamic pricing strategy.

The business model of the charging station operator proposed in this thesis is applicable for big parking lots such as the ones in office buildings or supermarkets. The revenues of the charging station operator come from charging of EVs and from participating in balancing grid services. The three stakeholders involved are charging station operator, grid operator and EV customers. Figure 3.1 illustrates the main activities of each stakeholder and key variable inputs needed for the charging station operation, in this example the grid operator is presented as National Grid, the transmission system operator in the UK. The charging station operator computes a bi-level optimisation where the charging station first estimates economical pricing schemes that are then followed by EV charging strategies. Both computations are important for the charging station and EV drivers, the pricing schemes ensure a financially sustainable operation of the charging station operator, and the EV char-

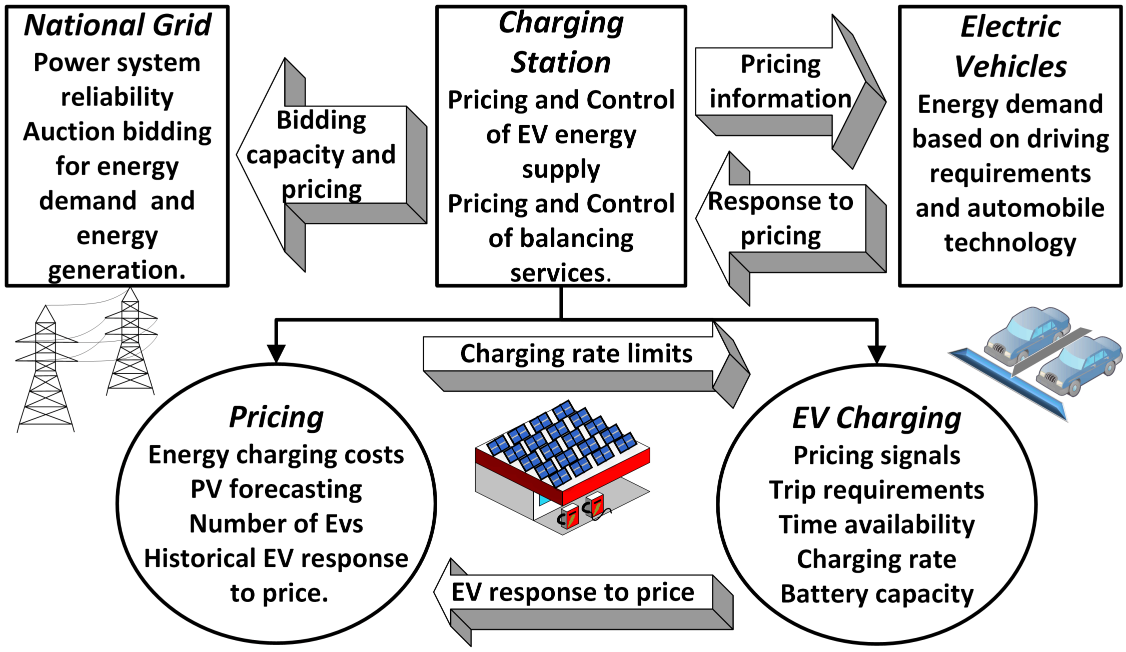


Figure 3.1: Proposed model with activities and communication between stakeholders involved and variable inputs for the pricing and EV charging optimisations.

ging module ensures customers save money as much as possible while complying with charging technology and customer restrictions. Consequently, the charging station operator is the price maker (monopoly case is assumed) that considers solar generation capacity, number of EVs in the charging station, energy price to buy from the grid when necessary and demand response of EVs to charging prices when setting pricing schemes. The EV charging module processes the charging strategies assuming customers will respond to price signals by charging when energy is cheaper and as long as restrictions like charging availability, driving requirements, charging and battery limits are ensured. The two modules in the bi-level optimisation are explained in more detail in the following subsections.

### 3.2.1 Time Of Use Dynamic Pricing

#### Dynamic Pricing

The pricing module is the first part of the model where prices are created when learning from historical price information used in advance. This price methodology uses the fundamentals of microeconomics of a monopoly where the EV aggregator is able to set prices and EV users are price takers. The model uses the information of price and demand curves, energy costs from the grid and stochastic onsite solar generation to use for EV charging, for every hour in a day. When looking closely at the stochastic variables of the model, the number of EVs in the charging station and variation of solar generation, the pricing model is able to compute a dynamic behavior of the tariff results for both pricing to announce to EV users and to a grid operator. The dynamic time of use tariff is called like this to refer to a combination of dynamic pricing and time of use pricing. Dynamic tariffs are commonly used for real time tariff applications, and time of use tariffs are popular in retail pricing as price based strategies in the area of demand response, these tariffs are made out of pricing for peak, off peak and middle peak periods (this last period is denominated optimum price in this Thesis). To compute dynamic pricing estimates, costs from energy used for charging EVs are estimated considering grid energy cost, and onsite generation at the charging station available for charging EVs. This dynamic pricing is then combined with a time of use tariff, which includes a highest, lowest and optimum pricing parts. Time of use pricing is estimated from revenue boundaries and charging station utilisation. Thus, a final dynamic time of use tariff is proposed to influence EV users to charge and to discharge accordingly. These pricing strategies are computed to make the operation of charging station economically feasible and to optimise revenues. The formulation of the pricing module considers the study of an average EV user $i$ and changes in the dynamics of the charging station in time $t$. The main goal of the EV aggregator in 3.2.1 is to find the optimum values of quantity $Q_t^*$ that will maximise utilities $u_t$ when evaluating revenues $r_t$ and costs $c_t$ for every hour in a day as follows,

$$\underset{Q_t}{\mathrm{Max}}\ u_t(Q_t) = r_t(Q_t) - c_t(Q_t) \tag{3.2.1}$$

The utilities are subject to the revenues at hour $t$ estimated by,

$$r_t(Q_t) = p_t(Q_t) \cdot Q_t. \tag{3.2.2}$$

The inputs for revenues are historical price $p_t$ and energy demand $Q_t$. To optimise for an optimum quantity, price is computed as a function of quantity from historical EV customer response to price represented as a linear regression by,

$$p_t(Q_t) = \beta_{0t} + \beta_{1t} \cdot Q_t, \tag{3.2.3}$$

where $\beta_{0t}$ and $\beta_{1t}$ are the corresponding coefficients from predicted price and charging demand estimations. The principles of this linear regression relationship are based on microeconomic theory [134; 135] that are key in the pricing scheme proposed to estimate better demand response pricing strategies, by computing a function of price and demand quantity (inverse demand curve). Microeconomic fundamentals are used in this chapter to measure predicted customer response to price from variations of historical charging demand and costs in a day. The values for $\beta_{0t}$ and $\beta_{1t}$ are obtained from real EV users charging rating quantities and time of use pricing used for "Electric Nation" project [136], more detailed information about these estimates are in simulation parameters subsection, in Evaluation of Case Studies section. The costs in 3.2.1 are computed from the cost of the charging station per energy unit to buy from the grid $cg_t$ and also taking into account the available onsite solar power generation $Ps_t$ per solar panel $n$, that can be used for charging available EVs at the charging station as below,

$$c_t(Q_t) = cg_t \cdot (Q_t - n \cdot Ps_t). \tag{3.2.4}$$

Thus, EV availability is studied as the available time $av_t$ an EV can be charged from arrival $ar$ to departure $de$ at the charging station according to EV driver behaviour in time $t$. Thus the availability of each EV is defined by,

$$av_t = \begin{cases} 1, & \text{if } ar \leq t \leq de \\ 0, & \text{otherwise.} \end{cases} \tag{3.2.5}$$

To find an optimal charging demand $Q_t^*$ from 3.2.1, following price and charging demand optimisation principles of microeconomic theory, it is required to equal marginal revenue $r_t'$ and marginal cost $c_t'$ as follows,

$$Q_t^* = arg(r_t' - c_t' = 0),$$

from the derivative of revenues and costs we obtain,

$$p_t'(Q_t) \cdot (Q_t) + p_t(Q_t) \cdot (Q_t') - cg_t = 0,$$

as we need to solve for $Q_t$, price terms are substituted as below,

$$\beta_{1t} \cdot Q_t + \beta_{0t} + \beta_{1t} \cdot Q_t - cg_t = 0,$$

after rearranging terms of $Q_t$ we obtain,

$$\beta_{0t} + 2 \cdot \beta_{1t} \cdot Q_t^* - cg_t = 0,$$

lastly when solving for $Q_t$ we get the optimal charging demand quantity below,

$$Q_t^* = (cg_t - \beta_{0t})/2 \cdot \beta_{1t}.$$

Given the optimal charging demand, we obtain the optimal price from the linear regression function estimated from historical demand as below,

$$p_t^* = \beta_{0t} + \beta_{1t} \cdot Q_t^*. \tag{3.2.6}$$

#### Time Of Use Pricing

As the charging operator aims to have an additional revenue stream to charging EVs which is obtained from bidding energy for balancing services, definition of both

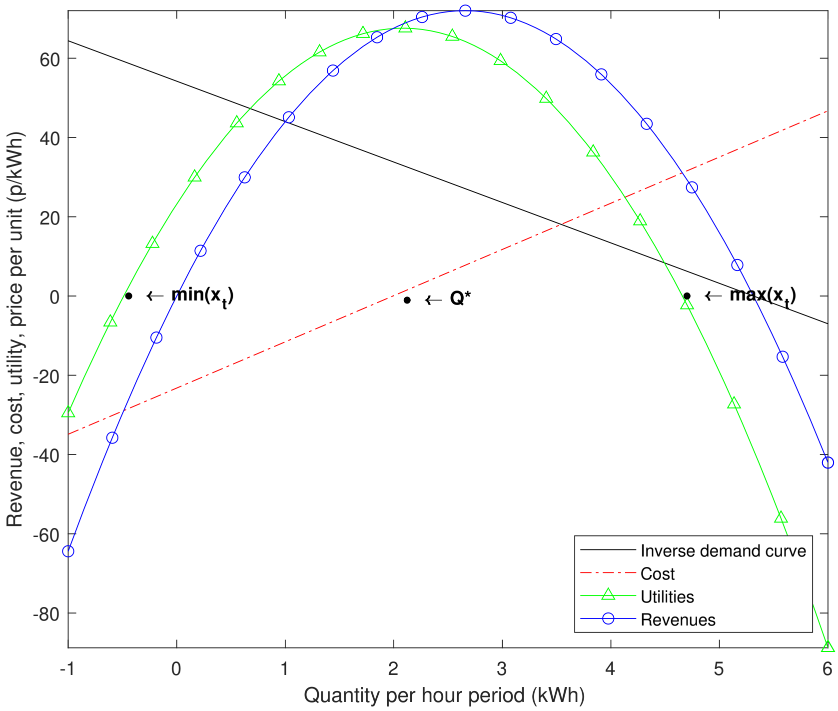


Figure 3.2: Mathematical relationship of variables in pricing optimisation.

profitable prices and charging ratings limits is key. Thus, if we define charging ratings as charging demand turn down as $Qd_t$, and demand turn up as $Qu_t$, the required charging ratings to have positive utilities must be within the following boundaries,

$$Qd_t \leq Q_t^* - \min(x_t), \tag{3.2.7}$$

$$Qu_t \leq \max(x_t) - Q_t^*, \tag{3.2.8}$$

where $min(x_t)$ and $max(x_t)$ state the minimum and maximum energy limits so that utility function $u_t(Q_t)$ is positive. Thus, these two quantity boundaries can be estimated from solving $u_t(Q_t) = 0$. To illustrate these boundaries, Figure 3.2 shows an example of the positions of $min(x_t)$, $max(x_t)$ as the utilities curve of the charging operator reaches zero, see equation 3.2.1. Note that point $min(x_t)$ has a negative charging rating quantity as onsite solar generation is included in costs, this explains the negative prices and negative chaging rating value in this point $min(x_t)$. It can also be observed in this graph the linear relationship between price and EV charging quantity denominated as inverse demand curve, equation 3.2.3, this is the basic reference for calculation of revenues and utilities. In addition to inverse demand curve, costs from equation 3.2.4, are also illustrated as a function of charging rating quantity. Revenues, equation 3.2.2, and utilities are also illustrated as functions of charging rating quantity when using equations to estimating price relationship to charging rating quantity and costs, as described before. When utilities reach a maximum point in relation to charging rating quantity, that is the point where the charging operator can optimise utilities, this optimum point is presented as $Q_t^*$ in the graph. The pricing optimisation use this optimum point to derive pricing strategies during a day.

To compute the demand response prices for the time of use dynamic tariff, the same linear regression for the optimum price is used. For practicality, energy balancing services when influencing EVs to charge more energy are referred as energy turn up, and energy turn down when influencing EVs to charge less energy or discharge energy with V2G technology. Calculations are made to find a profitable maximum and a minimum demand relation to price to provide incentives to EV customers. Prices for either energy turn down ($pd_t$) or energy turn up ($pu_t$) are estimated as follows,

$$pd_t = \beta_{0t} + \beta_{1t} \cdot (Q_t^* - Qd_t) \tag{3.2.9}$$

$$pu_t = \beta_{0t} + \beta_{1t} \cdot (Q_t^* + Qu_t). \tag{3.2.10}$$

The pricing matrix for the time of use dynamic tariff is computed from a combination of the optimum price and demand response prices, whenever is more convenient for the charging station to provide balancing services in a day, according to a charging station utilisation parameter $\rho_t$. The final price matrix ($pf$) is given by,

$$pf = \begin{bmatrix} p_1^* & \dots & p_{ti-1}^* & pd_{ti} & \dots & pd_{tf} \\ & \dots & pu_{tj} & \dots & pu_{te} & p_{te+1}^* & \dots & p_{24}^* \end{bmatrix}, \tag{3.2.11}$$

which is integrated from the optimum price ($p_t^*$) since the start of the day, where $p_1^*$ indicates the optimum price from hour 1, and before the time where energy turn down starts at $ti - 1$, then $pd_t$ and $pu_t$ prices are integrated accordingly to then go back to the optimal tariff from the end of the energy turn up period at $tf + 1$, and until the end of the day, where $p^*_{24}$ means optimum price until hour 24.

Utilisation parameter from the hourly capacity ($\rho_t$) of the charging station is considered in order to decide which timings are better for either providing energy turn down or energy turn up. The utilisation is classified in high ($h_t$), medium ($m_t$) and low ($l_t$) based on the charging availability between arrival and departure of EVs regardless of their charging status. Balancing services are provided only when capacity at the charging station is at high levels because the availability of EVs at the charging station is key to provide the corresponding flexibility services. The number of hourly periods at high level is divided by two periods with priority of providing cheaper tariffs to customer. For instance if there are 7 periods of time where there are parking spaces occupied with capacity greater than 2/3, then there are 3 time periods for energy turn down (higher prices) and 4 time periods for energy turn up (lower prices). Thus utilisation at the charging station is estimated by,

$$2/3 \cdot \rho_t \leq h_t \leq \rho_t \tag{3.2.12}$$

$$1/3 \cdot \rho_t \leq m_t \leq \rho_t \cdot 2/3 \tag{3.2.13}$$

$$0.1 \cdot \rho_t \leq l_t \leq \rho_t \cdot 1/3. \tag{3.2.14}$$

The next stage for pricing calculation is the computation of prices for participation in balancing services in auction mechanisms, for instance the ones to announce to National Grid in the UK. Flexibility service companies are expected to provide price, capacity and timings for energy turn down or energy turn up provision [137]. Given the structure of the market, the EV aggregator is able to provide prices and bidding quantities. The expectation is that balancing services are used as additional revenue streams. Consequently, the utilities obtained from National Grid should balance the loss of revenues of EV charging when using the demand response prices $pd_t$ and $pu_t$, in other words when deviating from the optimum price and quantity. Therefore, prices to announce to National Grid are computed based on equivalent revenue deviations from the optimal revenue from EV charging. The price estimation is computed from making equal optimum utilities ($u_t^*$) and expected utilities to obtained from National Grid for energy turn down ($u_{1t}$) and energy turn up ($u_{2t}$) as below,

$$u_t^* = u_{1t} \tag{3.2.15}$$

$$u_t^* = u_{2t}, \tag{3.2.16}$$

where utility functions for energy demand turn down and turn up can be given by,

$$u_{1t} = \begin{cases} pgd_t \cdot |Qd_t| - pd_t \cdot |Qd_t|, & \text{if } Qd_t \leq 0 \\ pgd_t \cdot Qd_t - cg_t \cdot (Qd_t - n \cdot Ps_t), & \text{otherwise} \end{cases} \tag{3.2.17}$$

$$u_{2t} = pgu_t \cdot Qu_t - cg_t \cdot (Qu_t - n \cdot Ps_t). \tag{3.2.18}$$

The costs for energy turn down in 3.2.17 vary when it is economically possible to discharge an EV, in this case the corresponding costs are energy paid to EV users. In the case when the charging rate is positive, costs are estimated according to grid energy costs and available solar power at the charging station.

Thus, the prices for bidding energy for balancing services of energy turn down $pgd_t$ and energy turn up $pgu_t$ are computed as follows,

$$pgd_t = \begin{cases} \frac{u_t(Q_t^*) + pd_t \cdot |Qd_t|}{|Qd_t|}(1+\delta), & \text{if } Qd_t \leq 0 \\ \\ \frac{u_t(Q_t^*) + cg_t \cdot (Qd_t - n \cdot Ps_t)}{Qd_t}(1+\delta), & \text{otherwise} \end{cases} \tag{3.2.19}$$

$$pgu_t = \frac{u_t(Q_t^*) + cg_t \cdot (Qu_t - n \cdot Ps_t)}{Qu_t}(1+\delta). \tag{3.2.20}$$

The calculations of these prices are obtained when solving for $pgd_t$ and $pgu_t$ from the substitution of 3.2.17 and 3.2.18, in 3.2.15 and 3.2.16. To allow a profit from participating in balancing services, a margin of utility $\delta$ is added to National Grid prices $pgd_t$ and $pgu_t$ to cover for additional complexities of management control. This is a reasonable addition to pricing because the charging station sets prices for bidding in an auction market considering a cost based strategy.

### 3.2.2 EV Charging Control

The control model which is used for planning of energy bids to submit to the grid operator (National Grid), is constructed to follow pricing signals received from the charging station operator in a day ahead timeline, by minimising costs from charging an EV. The control model, which was initially inspired by the work of Sortomme *et al.* [79], has been adapted to be able to work with different charging rates limits, battery state of charge (SOC) restrictions and stochastic variables for EV requirements. These additions allow accurate simulations of driver behavior during a day with different charging capabilities. The objective function of the charging control is the minimization of costs ($c_i$) for the complete charging period the $i$th EV parked at the charging station given by,

$$\underset{q^*_{i,t}}{\text{Min}}\ c_i = \sum_{t=1}^{T} pf \cdot q_{i,t}, \tag{3.2.21}$$

where the charging rate $q^*_t$ is the decision variable in the formulation that determines the charging schedule of each EV every hour. This decision variable can become negative and discharge the EV battery when the charging station aims to provide balancing services to the grid and when the EV is conveniently available for discharging. It is expected that EVs will get not only positive values from the costs in the objective function but also negative values (EV revenues) when getting paid for V2G provision if allowed.

To meet technology constraints of the charging station and the EV, we define the charging rate limits for the charging schedule with $a_t$, as the maximum charging rate and $b_t$, as the minimum charging rate of $q_t$ when evaluating the charging rate of an EV ($y_t$) and charging rate of the charging station pole ($z_t$) as below,

$$a_{i,t} = \min(y_{i,t}, z_{i,t}) \tag{3.2.22}$$

and

$$b_{i,t} = \max(-y_{i,t}, -z_{i,t}). \tag{3.2.23}$$

The state of charge of the EV is also considered, where $soc_{i,t}$ is $i$-th EV's battery state of charge at time $t$ that considers charging efficiency $ef$ when charging rate is positive $q^+_{i,t}$ or negative $q^-_{i,t}$ as follows,

$$soc_{i,t} = soc_{i,t-1} + q^+_{i,t} \cdot ef + q^-_{i,t} \cdot (2 - ef) \tag{3.2.24}$$

Note that efficiency is modelled from the charging operator perspective, where it has to charge more energy, and discharge less energy to avoid taking advantage of EV users over payment charges, and to balance power losses. For instance, for 7.2 kW charge with 0.9 of charging efficiency, the charging operator should provide charging of 10% more of 7.2 kW, and for discharging, the charging rate should be 10% less charge than the optimum charging rate metered in the charging station pole. Consequently, charging optimisation limits $q_{i,t}$ are subject to,

$$\begin{cases} q_{i,t} \geq b_{i,t} \cdot av_{i,t}, & \text{if } q_{i,t} \leq 0 \\ q_{i,t} \leq a_{i,t} \cdot av_{i,t}, & \text{if } q_{i,t} > 0 \end{cases} \tag{3.2.25}$$

where $av_{i,t} = \{0 \text{ or } 1\}$ is a binary matrix per EV that states its availability (arrival to departure) at the charging station as described in the pricing optimisation. The usage of the charging rate limits in 3.2.25 allow the modeling of charging and discharging constraints for specific periods of time and thus, allow the modelling of V2G and G2V technology. Battery size limits $w_i$ are ensured by taking into account the state of charge of an EV by,

$$0.01 \cdot w_i \leq soc_{i,t} \leq w_i. \tag{3.2.26}$$

EV trip requirements are formulated when calculating state of charge (energy levels) by,

$$trip_i = socf_i - soci_i, \tag{3.2.27}$$

where $soci$ is the initial state of charge and $socf$ is the final state of charge of an EV.

### 3.2.3 Vehicle to Grid and Grid to Vehicle Analysis

Benefits for the charging station operator come from two revenue streams: when selling energy to EV customers, and when participating in balancing services markets after aggregating EVs' scheduling, while benefits for EV customers come from savings when charging their EVs, following cheaper pricing periods, and from selling energy to the charging operator, following high pricing periods. To evaluate potential charging operator utilities from the price strategy proposed in the time of use dynamic pricing subsection, the responses to prices from EV drivers described in the EV charging control subsection are evaluated against V2G (bidirectional) and G2V (unidirectional) technology. As described before, the EV charging control optimisation can evaluate charging rate restrictions for both unidirectional and bidirectional charging. Thus, given the different charging rate of the EVs, revenues and costs vary as well as the interactions with the available solar power generation at the charging station. The time of use dynamic tariff can be used for testing EV driver response according to current technology available in the market. The utilities of the charging station operator with V2G technology ($u_{vg}$) and G2V technology ($u_{gv}$) are computed in equations 3.2.28 and 3.2.29. These include revenues associated to each technology.

$$u_{vg} = r_{vg} - c_{vg} \tag{3.2.28}$$

$$u_{gv} = r_{gv} - c_{gv} \tag{3.2.29}$$

Revenues with V2G technology capability ($r_{vg}$) are integrated from sales coming from aggregated bidding for energy turn up (first term), energy turn down (second term) and EV charging (third term) when the charging rate is positive ($q_t^+$) by,

$$r_{vg} = \sum_{i=1}^{I} \left\{ \sum_{t=tj}^{te} pgu_t \cdot q_{i,t} + \sum_{t=ti}^{tf} pgd_t \cdot q_{i,t} + \sum_{t=1}^{24} pf \cdot q_{i,t}^{+} \right\}, \tag{3.2.30}$$

where $I$ is the set of EVs to be charged by the charging station operator. Balancing service timings are defined by an initial hour $tj$ and $ti$, and final hour $te$ and $tf$ for energy turn up and turn down periods respectively. Costs for providing balancing services with V2G technology capability come from energy paid to EV users when the charging rate is negative ($q^{-}_{i,t}$), and when energy must be bought from the grid ($q^{+}_{i,t}$) when referencing to available solar power generation at the charging station, as below,

$$c_{vg} = \sum_{i=1}^{I} \left\{ \sum_{t=1}^{24} pf \cdot |q^{-}_{i,t}| + \sum_{t=1}^{24} cg_t \cdot (q^{+}_{i,t} - P_{i,t}) \right\}, \tag{3.2.31}$$

where $P_{i,t}$ is the average available solar energy that can be used to charge an EV which can be estimated by,

$$P_{i,t} = n \cdot Ps_t / \sum_{i=1}^{I} av_{i,t}. \tag{3.2.32}$$

In contrast, revenues from provision of balancing services with G2V technology capability come from sales from energy turn up and sales from EV charging by,

$$r_{gv} = \sum_{i=1}^{I} \left\{ \sum_{t=tj}^{te} pgu_t \cdot q_{i,t} + \sum_{t=1}^{24} pf \cdot q_{i,t} \right\}. \tag{3.2.33}$$

Compared to V2G technology costs, G2V costs come only from buying energy from the grid when needed as below,

$$c_{gv} = \sum_{i=1}^{I} \sum_{t=1}^{24} cg_t \cdot (q_{i,t} - P_{i,t}). \tag{3.2.34}$$

To illustrate the complete transactions of a charging operator during a day, Figure 3.3 presents an algorithm flow chart with the processes involved, starting with data acquisition and forecasting to produce inputs of the pricing and EV charging optimisation. Then the charging operator uses the pricing and EV charging optimisation to compute the bidding prices and quantities for balancing services, as well as the prices for EV charging users. Finally, the charging station operator can compare utilities obtained based on the technology used for EV charging.

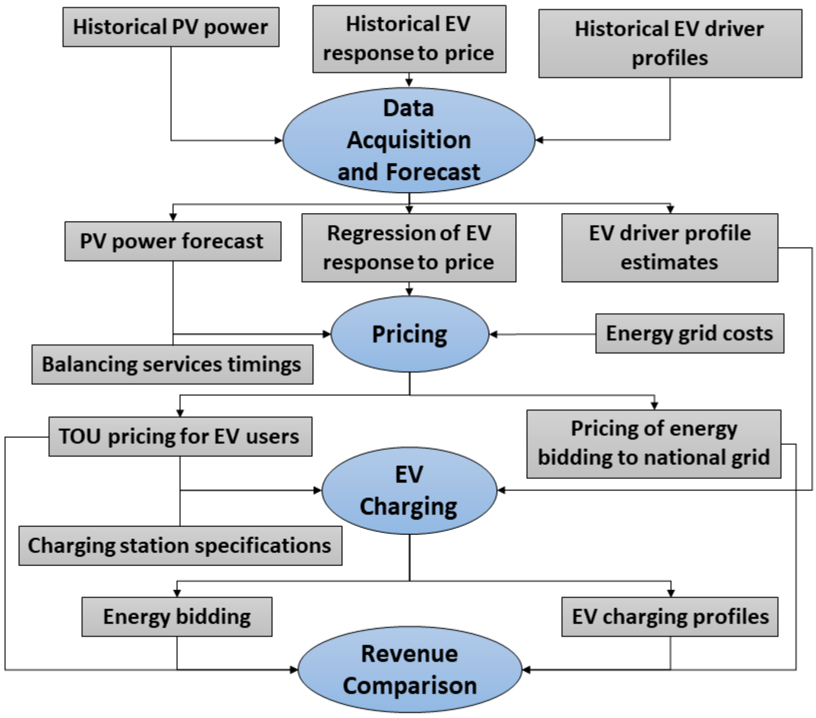


Figure 3.3: Algorithm flow chart of charging operator operations in a day.

## 3.3 Evaluation of Case Studies

### 3.3.1 Simulation Parameters

Table 3.1 summarizes the simulation parameters which are described in the following paragraphs. To test the TOU dynamic pricing and the EV charging control optimisation algorithms, different cases are proposed to show applicability of the model to real case scenarios and to compare EV charging business models with balancing services. As the charging speed rating increases with EV charging types, the price for providing energy may also increase. In addition, customers may respond to prices differently, for example when there is competition in an area or when EV drivers change charging behavior. To take into account these possibilities, the pricing strategies are evaluated with different different elasticities of three inverse demand curves; an original demand from real data, a theoretical more elastic and a more inelastic demand. The original demand curve is also used to create demand curves when testing for increasing charging rates. The EV charging control algorithm is

Table 3.1: Simulation parameters

| Parameter | Value |
|---|---|
| Charging station size | 35 EVs |
| Time periods in a day | 24, for every hour |
| EV arrivals | $ar \sim \mathcal{N}(\mu = 8,\, \sigma^2 = 1)$ [138] |
| EV sojourn time | $ts \sim Logistic(\mu = 0.27,\, s = 0.06), mn = 5, mx = 18.52$ [138] |
| Solar panel rating | 4 kW [139] |
| Number of solar panels | 70 |
| Initial state of charge | Empirical cdf [140] |
| Trip requirements | Empirical cdf [140] |
| Fast charging 1, 2 and rapid ratings | 7, 22 and 50 kW [141] |
| Mitsubishi Outlander charging ratings/battery size | 3.7 and 22 kW/ 12kWh[142] |
| Nissan Leaf charging rating/battery size | 6.6 and 50 kW/40 kWh[143] |
| BMW 330e charging ratings/battery size | 3.7 kW/12 kWh[144] |
| Tesla 3 charging ratings/battery size | 11 and 100 kW/60kWh [145] |
| Electricity price | 10 p/kWh [146] |
| Utility from balancing services | 10% |

used to test EV responses to prices and energy bidding capacity, the results are evaluated comparing the capability of V2G and G2V technology.

EV driver behavior was generated from real world projects to provide accurate simulations. Fig. 3.4 shows stochastic number of EVs available for charging from an aggregated availability matrix of all EVs for the specific case of charging at work. This figure was generated considering a total of 35 EVs. For simulation purposes, EV profiles are created with 30, 35 and 25 EVs that arrive at the charging station in a 24 hour period assuming demand changes from an original, more elastic and more inelastic demand curves respectively. The EV profiles were created from EV arrivals ($ar$) and sojourn timings ($ts$), defined as departure minus arrival time, from the work analyzed by Develder *et al.* [138]. The available onsite power generation forecast with an hourly average of all seasons, illustrated in Fig. 3.5, and size of the solar system were obtained from [139]. Definitions for initial state of charge of EVs and trips were estimated with empirical distribution functions using EV charging data of the workplace cluster information from "My Electric Avenue" project [140], kindly

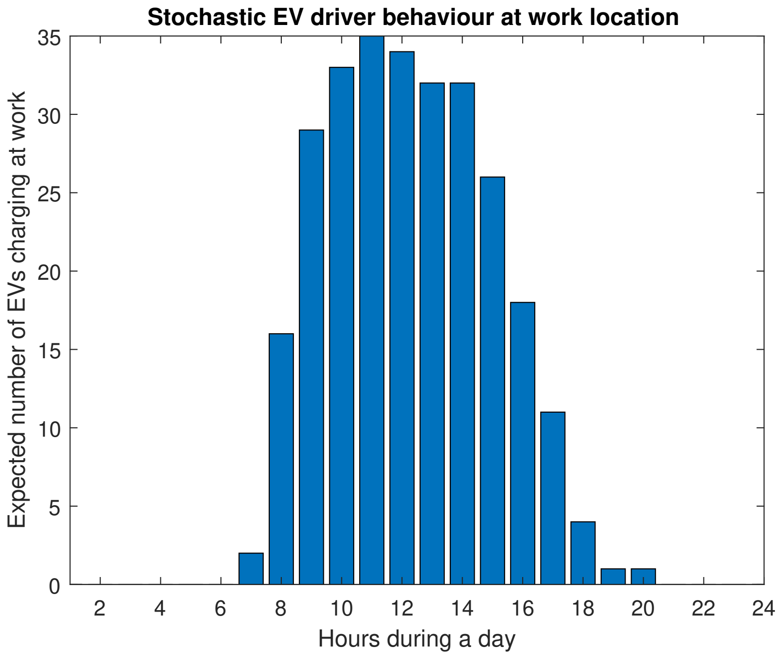


Figure 3.4: Stochastic number of EVs at the charging station for workplace location.

provided by EA technology. Charging rate limits for both the charging station and EVs use two selected charging rates of fast charging and one from rapid charging as explored in [141]. The percentage mix of EVs in the simulation used parameters of charging rates and battery size of Mitsubishi Outlander PHEV (40%), Nissan leaf (30%), BMW 330e (20%) and Tesla 3 (20%).

The demand and price curves that form the inverse demand curve of the case study were estimated with 40 observations with results showing significant coefficients with a p value close to zero of the linear regression model and an adjusted R-squared value of 0.815. Raw data for these calculations were estimated using real data from trial 3 of "Electric Nation" project [136], also provided by EA Technology. To estimate elasticity variations to price from EV drivers, the coefficients in the demand curve were decreased and increased by a third in order to create a more elastic and more inelastic demand curves. Prices and demand data sets for different charging rates were multiplied by 1/2 (fast charging 2), 2/3 (rapid charging) for price, and by 4 (fast charging 2), 10 (rapid charging) for demand in order to match prices close to real data in the current market available in [147]. The cost for energy from the grid

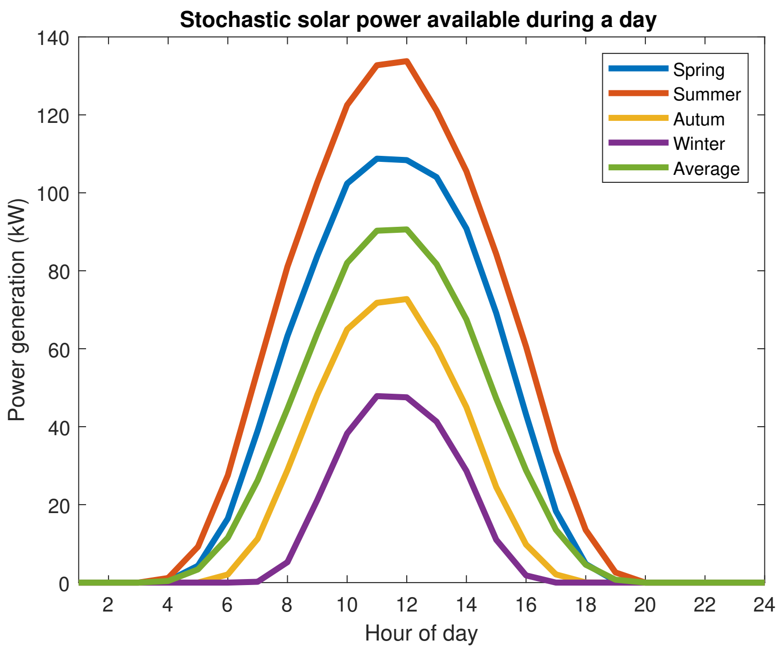


Figure 3.5: Stochastic available PV generation at the charging station during different seasons.

was assumed to be fixed at a rate of 10 p/kWh (pence per kilowatt hour) as proposed in [146]. Once the profiles for driver behavior, PV forecast and demand curves are created, the pricing and EV charging optimisations are used to compute results for the cases where demand curve elasticity changes as well as charging speed varies with V2G and G2V technology. The pricing and EV charging optimisations are solved in MATLAB, the linear programming of the EV charging control is formulated using Yalmip toolbox [148] and solved with Gurobi [149]. The model is solved in a computer with processor Intel 3.40GHz core i7 and 32 GB of RAM memory. Analysis and discussion of results are presented in the next two sections.

In summary, inputs required for both pricing and EV charging optimisation as well as solver methods were described in the previous paragraphs. To compute the pricing optimisation, inputs required with detailed explanation of stochastic EV profiles, inverse demand curve with 3 different price and demand (elasticity variation), onsite power generation forecast and expected utility percentage were described. Similarly, inputs for EV charging with detailed estimates of stochastic EV charging profiles, EV charging ratings, EV battery size and charging rating mix were described. Results of: the pricing optimisation with stochastic variables, the EV optimisation based on EVs response to price and expected utilities, revenues and costs is presented in Sections 3.3.2 to 3.3.4.

### 3.3.2 Pricing with Stochastic Variables

The merits of the pricing and EV charging algorithm are evaluated in this section to show their potential usage in different EV driver demand response behavior with three different elasticity levels of inverse demand curves and different charging technology with three charging speeds and V2G/G2V capabilities. Processing time for the computation of each pricing strategy is 14 s, and for EV charging optimisation schedules with V2G is 58.4 s and with G2V is 49.1 s. This is a reasonable processing time as pricing and energy bidding capacity is estimated as a day-ahead planning horizon. Figures 3.6 and 3.7 illustrate the pricing fundamentals and the dynamic TOU pricing strategies for EV charging. Figures 3.8 - 3.13 illustrate the EV charging profiles and potential for bidding during energy balancing timings. Figure 3.14 shows a comparison of EV profiles with a fixed tariff. Figures 3.15 and 3.16 are a representation of sources of revenues and costs. Finally, figure 3.17 compares expected utilities from all case scenarios. A comprehensive analysis of each graph is described in the following paragraphs.

Figure 3.6 is a representation of the basic functions used for calculation of the different pricing strategies that include an inverse demand curve, revenues, costs and utilities. The three examples of inverse demand curves presented in Figure 3.6 are the base (original curve) used to derive evaluation of cases when creating pricing schemes for fast charging 1, fast charging 2 and rapid charging. The original inverse demand curves for the fast charging 1, fast charging 2 and rapid charging scenarios present the different responses to prices from an average EV at any time. The three inverse demand curves show that as prices increase per kWh, EVs would respond with charging less energy and as price decreases EVs would aim to charge more

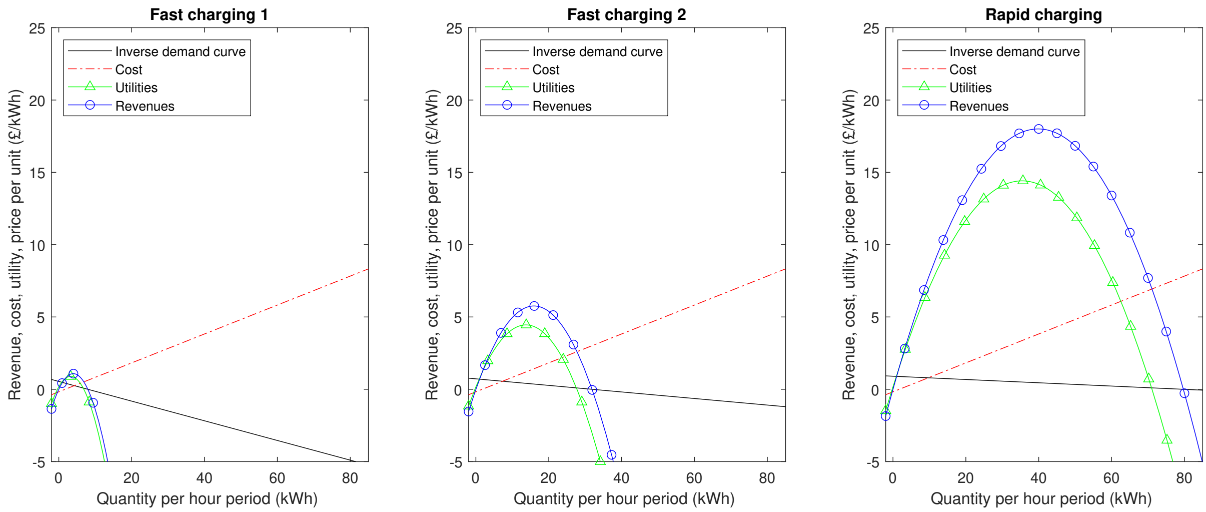


Figure 3.6: Inverse demand response, utilities, revenues and costs of EV charging for three different charging ratings.

energy. The figure also shows more average revenues and utilities are obtained from rapid charging compared to fast charging 2, and more with fast charging 2 compared to fast charging 1. An explanation of this trend is a result of using higher prices and quantities with faster services of EV charging. The costs for the three charging ratings remain the same as the three cases assume the same fixed energy cost per energy unit and the same available free energy from onsite solar generation power to charge EVs.

The proposed time of use dynamic tariff in this paper includes tariffs for periods of peak, off peak and normal hours. Peak and off peak periods during a day are intended to be synchronized with timings for balancing services for energy turn down and energy turn up requirements, other timings are irrelevant for balancing services purposes. Figure 3.7 shows that in the cases of the original demand curve, from 9:00 to 11:00 hours energy is more expensive and from 12:00 to 14:00 hours energy is cheaper. Timings with the more elastic curve are increased by one hour when energy is cheaper compared to timings with the original curve. Timings with the more inelastic curve are reduced by one hour in both expensive and cheap timings compared to timings with the original curve. The reason for these changes are related to availability of demand with different EV numbers determined by price

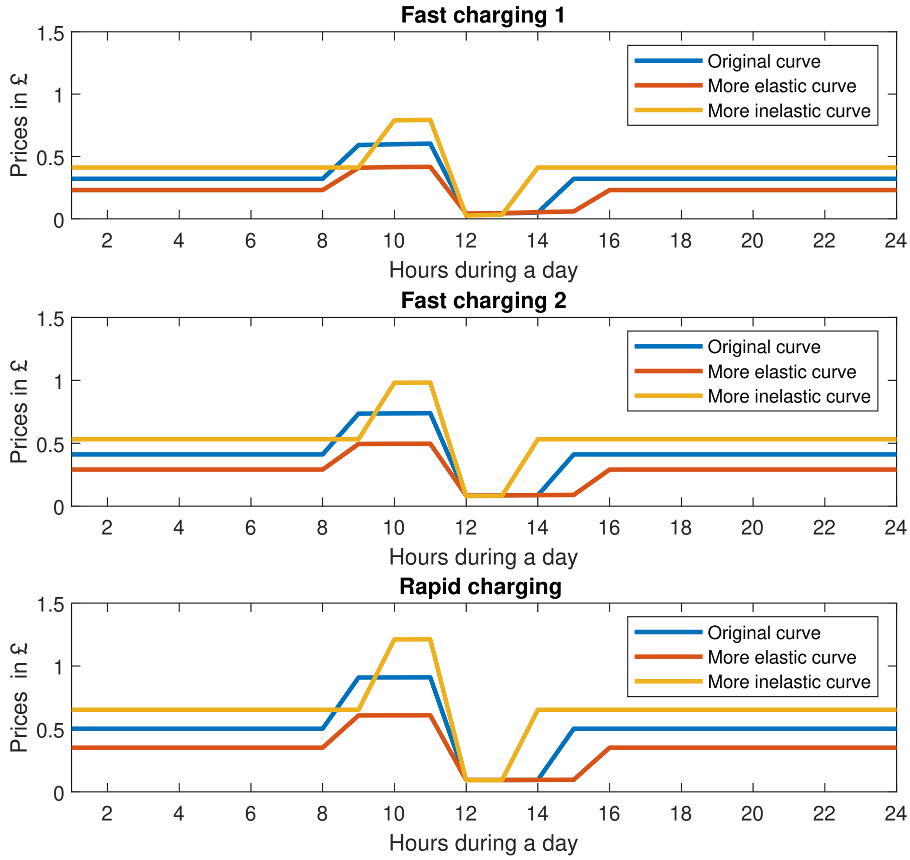


Figure 3.7: Dynamic time of use tariffs used to incentivise EVs based on demand inverse curves and charging type cases.

elasticity where balancing timings are set when there is sufficient capacity at the charging station as established by the pricing algorithm. The three cases where energy is obtained with an original curve, a more elastic and more inelastic curve aim to represent changes from demand. This is an essential consideration for demand response mechanisms, because knowing how customers will respond to pricing and by which quantity is critical to determine an appropriate use of tariffs for balancing services. The different elasticity cases for each different inverse demand curve could represent when EVs may be subject to substitution effects, for instance when EVs have other options in the area for charging (elastic demand), or when EVs prefer charging from one specific day of the week for personal preference regardless of price (inelastic demand). The results of the dynamic time of use pricing strategy illustrated in 3.7 adapt accordingly with varying requirements of demand elasticity,

Table 3.2: Dynamic Time of Use Pricing Summary

| Charging rating | Elasticity level | Normal price (p/kWh) | Off-peak price (p/kWh) | Peak-price (p/kWh) |
|---|---|---|---|---|
| Fast charging 1 | Original | 32.1 | 3.8, 4.4, 5 | 59.1, 59.8 ,60.3 |
| | More elastic | 23.1 | 4.3, 4.5, 5.3, 5.9 | 40.9, 41.5, 41.7 |
| | More inelastic | 41.1 | 2.6, 3.3 | 79, 79.4 |
| Fast charging 2 | Original | 41.1 | 8.4, 8.5, 8.7 | 73.5, 73.7, 73.9 |
| | More elastic | 29.1 | 8.5, 8.6, 8.7 | 49.5, 49.6, 49.7 |
| | More inelastic | 53.2 | 8.1, 8.2 | 98.1, 98.2 |
| Rapid charging | Original | 50.2 | 9.4, 9.4, 9.5 | 90.8, 90.9, 91 |
| | More elastic | 35.1 | 9.4, 9.4, 9.5, 9.6 | 60.7, 60.8, 60.8, |
| | More inelastic | 65.2 | 9.2, 9.3 | 121.2, 121.2 |

timings for balancing services and charging rating.

The prices during balancing services change slightly with cost variation due to available onsite generation of energy per each EV. Table 3.2 presents more granular price units in p/kWh and more detailed structure of the dynamic time of use tariffs of fast charging 1, fast charging 2 and rapid charging ratings when using an original, a more elastic, and more inelastic inverse demand curves. This detailed structure is made of a normal price with a constant price with off-peak and peak-prices during different timings throughout the day. Note that the normal price covers the majority of price timings, the peak and off-peak prices cover from 2 to 4 periods each depending on the charging rating and inverse demand curve used. The normal price is constant as it is the optimal price derived from utility optimisation, and the off-peak and peak-prices mark the limits for maximum and minimum the charging station operator is willing to offer in exchange of demand response expected from EV users. In comparison with the normal price, off-peak and peak-prices have variation as they consider availability of onsite solar power every hour. A combination of the normal price, off-peak price and peak-price is the tariff that is used for announcing pricing tariffs for EV users which is used used as a symmetric price used for selling energy to EV users and for buying energy from EV users.

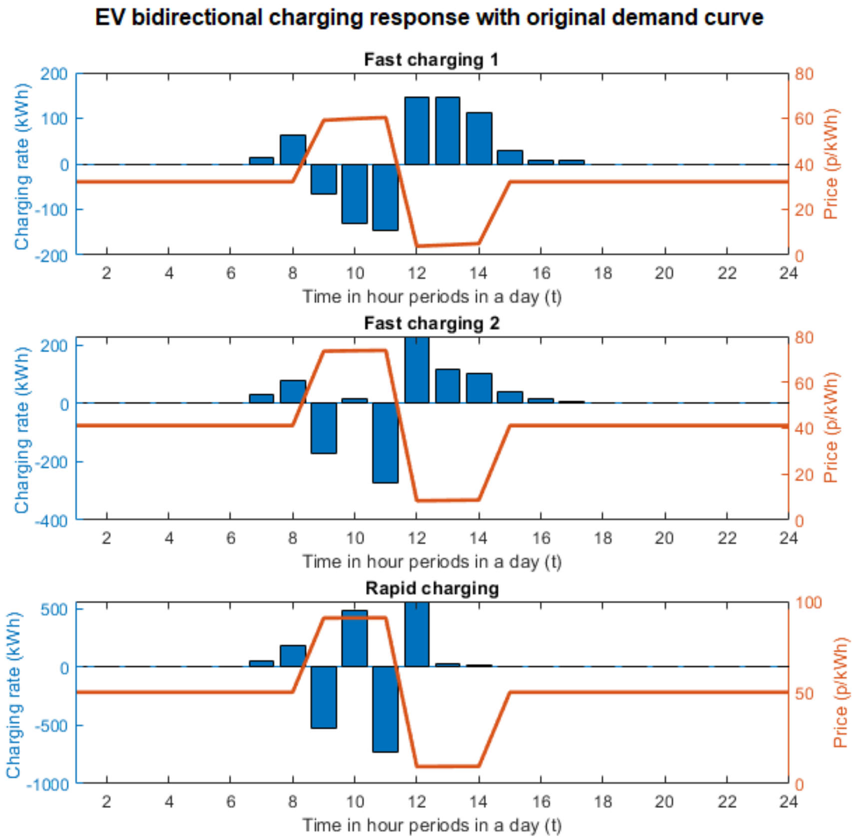


Figure 3.8: EV charging profiles as a response to prices with original demand curve using different charging type cases and bidirectional capability.

### 3.3.3 EV Response to Price

Figure 3.8 shows the response from EVs with V2G capability at different charging rates. Fast charging 1 limitations for EV charging shows EVs discharge energy when energy is expensive, this allows EVs to get paid for energy provision to the grid at a high price, a reasonable consideration for battery compensating for degradation when using V2G technology. The charging rate during energy turn down period with fast charging rate 1 is negative and therefore balancing services can be provided from 9:00 hrs to 11:00 hrs. However, this changes with fast charging rate 2 because EVs can take more advantage of savings when buying energy at 10:00 hrs to then discharge power at 11:00 hrs. Similarly, rapid charging allows EVs to charge at 10:00 hrs to then discharge at 11 hrs with a greater energy bid at 9:00 hrs and 11:00 hrs compared to fast charging 1 and 2. During energy turn up periods, EVs

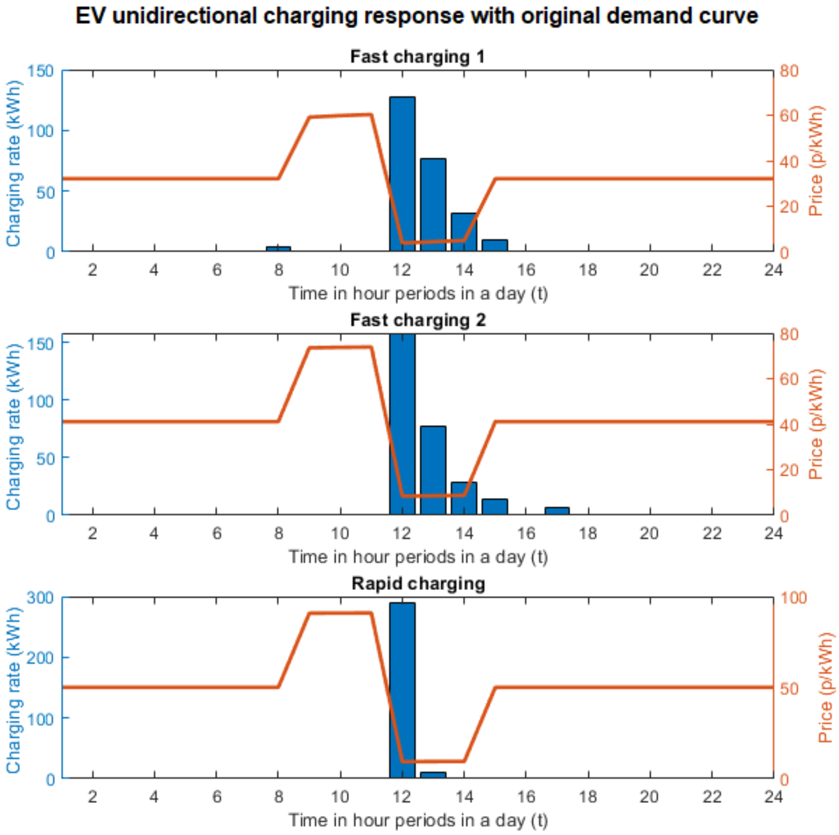


Figure 3.9: EV charging profiles as a response to prices with original demand curve using different charging type cases and unidirectional capability.

charge energy taking advantage of the cheap prices. As the charging rate increases EVs charge with the required trip requirements faster. Charging outside balancing services occur in case driver requirements were not met by the end of the turn up period which is the case of fast charging 1 rating. Rapid charging has the biggest bid per hour followed by fast charging 2 and fast charging 1. It is important to point that a smaller charging rate could maintain more average capacity for longer periods of time as it is observed in fast charging 1 and 2 charging rate cases. However, bidding potential occurs for fewer periods of time with higher charging ratings as trip requirements are met at a higher speed.

To continue with the responses results of EV drivers, Figure 3.9 illustrates the EV aggregated charging schedule when EVs have unidirectional charging and using an original demand curve for pricing. EV profiles show the majority of EV charging

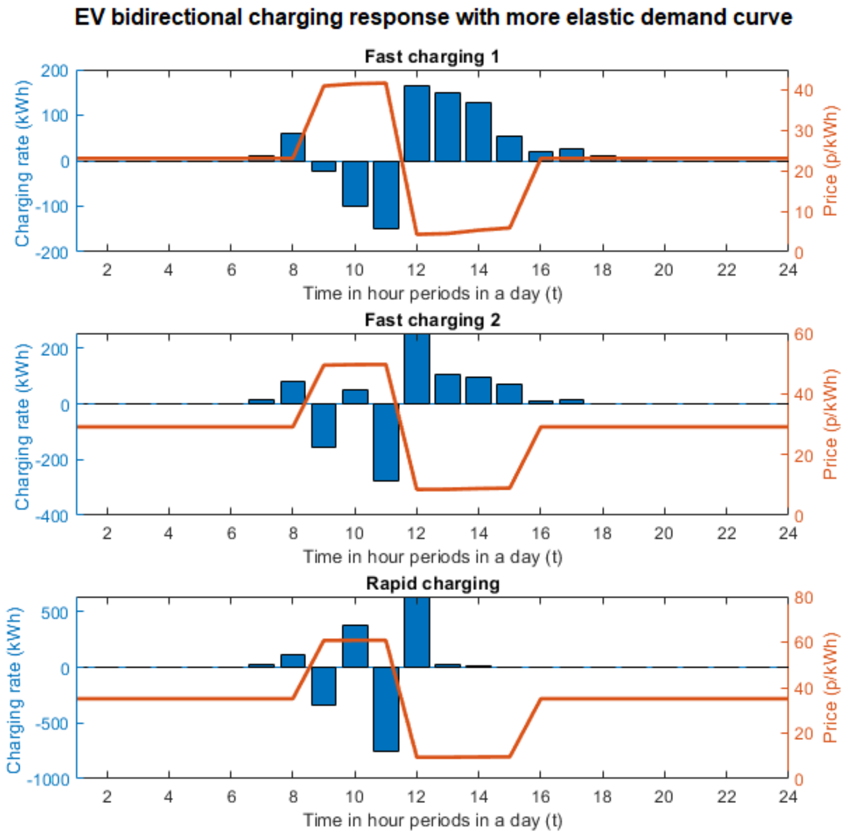


Figure 3.10: EV charging profiles as a response to prices with more elastic demand curve using different charging type cases and bidirectional capability.

happens when energy is cheaper, which is also when energy turn up provision is needed. However, aggregated biding for every hour is not greater than the V2G option as charging is employed to meet energy requirements without the need to discharge EVs. The charging scheduling is concentrated at 12:00 hrs as availability at the charging station indicates EVs need to be charged before expected departures. Similar to the V2G case, a greater energy bid is performed with rapid charging, followed by fast charging 2 and 1 respectively. It can also be observed in 3.9 that the charging schedule of fast charging 1 and 2 indicate some charging needs to happen outside turn up periods. Thus a greater charging rate is needed to fully take advantage of getting revenue from charging and for participating in balancing services at the same time. When comparing the overall charging schedules from figures 3.8 and 3.9 we can see that V2G offers greater hourly bidding capacity for

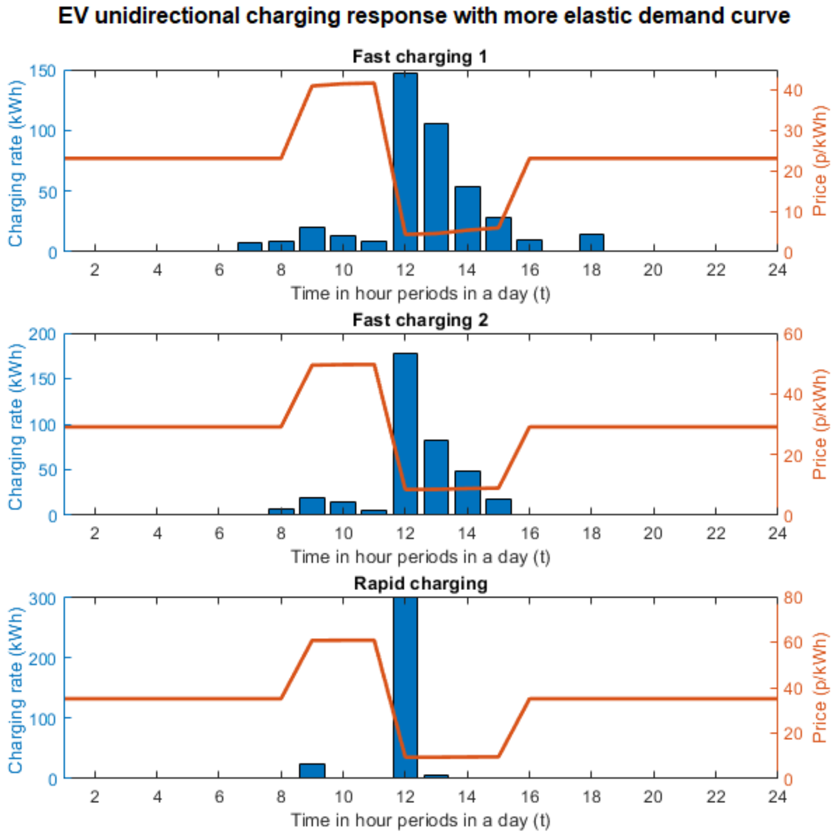


Figure 3.11: EV charging profiles as a response to prices with more elastic demand curve using different charging type cases and unidirectional capability.

both energy turn down and energy turn up. This can be attributed to the possibility to discharge an EV and charge it again when needed at later times as opposed to just charge it to meet trip requirements with unidirectional charging. Thus energy bid capacity is more limited with unidirectional technology but it is still feasible to have some bidding capacity during turn up period.

Figures 3.10 and 3.11 were created with new stochastic EV profiles from an average user type with a more elastic demand curve, the aim of the pricing scheme is to attract more EV users to the charging station, for instance when there is competition or when the charging station aims to influence EV users to charge at a specific day of the week. Figure 3.10 shows that overall energy bidding capacity for energy turn up is greater compared to the original demand curve EV profiles as there are more cars which are influenced to arrive at the charging station. However, most

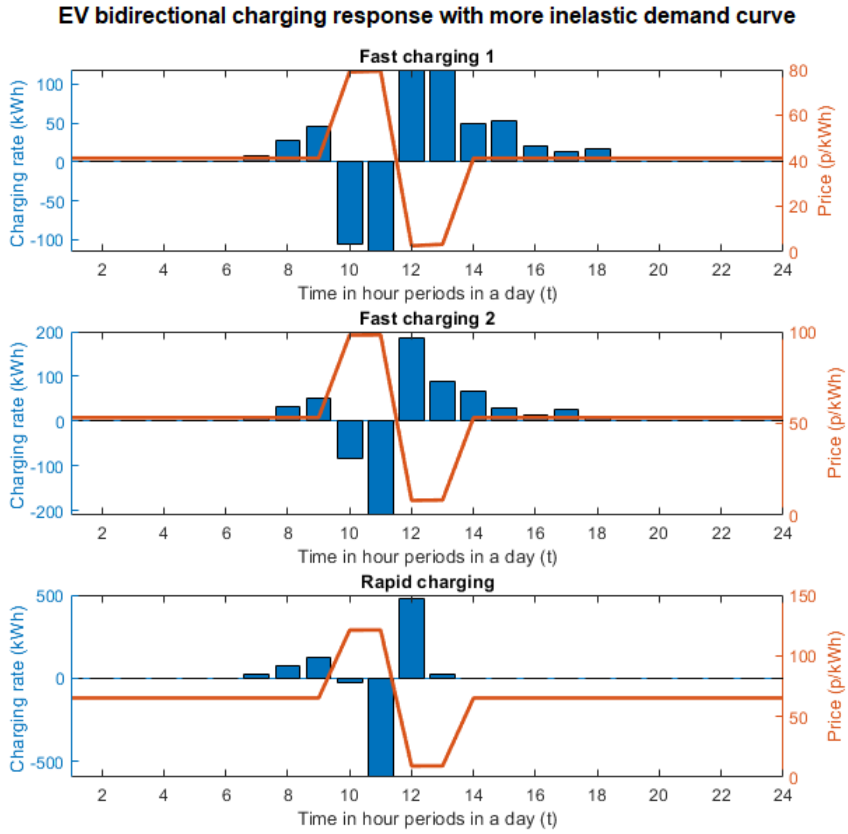


Figure 3.12: EV charging profiles as a response to prices with more inelastic demand curve using different charging type cases and bidirectional capability.

periods for energy turn down of Figure 3.10 are smaller compared to 3.8, this means EVs optimise revenues by taking advantage of the extended turn up periods (cheap energy). Greater bidding capacity is achieved with rapid charging, however for less periods of time compared to fast charging 1 and 2. The energy bids for fast charging 1 and 2 overall have less capacity than the ones with rapid charging but they are still able to provide energy to turn up balancing services from 12:00 hrs to 15:00 hrs. The extension of cheap prices during energy turn up periods compared with the original curve results could mean that with the more elastic curve results, EVs have more cost savings, however EV revenues obtained from energy to sell to the charging station should also be considered.

Figure 3.11 shows the unidirectional charging strategies with a more elastic EV demand curve. It can be observed that most charging would happen during energy

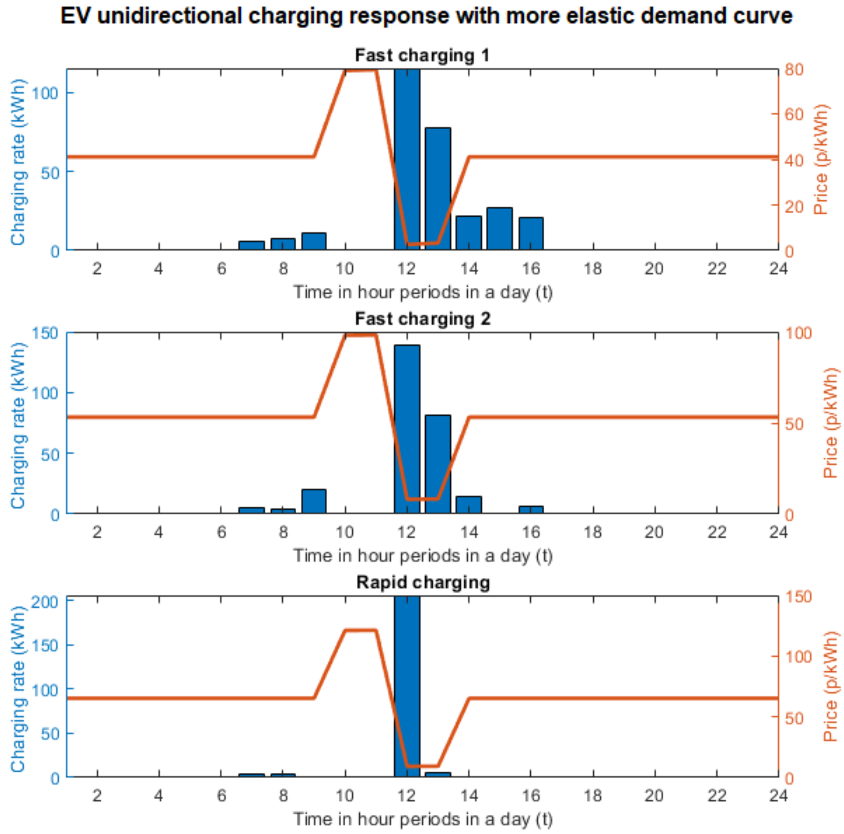


Figure 3.13: EV charging profiles as a response to prices with more inelastic demand curve using different charging type cases and unidirectional capability.

turn up periods. In the results obtained with fast charging 1 rating some EVs should be charged after 15:00 hrs as the charging rate is too slow to allow to charge all EVs during the cheaper periods. It is important to note that some charging must happen during turn down period in order to meet driver requirements, thus this energy would not be used for balancing services and the charging station would only receive money from charging EVs during this balancing service period. These results can be explained by the limitations of unidirectional charging to meet EV trip requirements and availability of EVs at the charging station for being used as flexibility loads. Similar to the EV profiles obtained in Figure 3.10, there is greater bidding for energy turn up period in Figure 3.11 (with a more elastic demand curve) compared to Figure 3.9 (with the original demand curve) as there are greater number of EVs charging and more incentives for charging during cheaper periods.

Figures 3.12 and 3.13 show the charging profiles resulted from using a more inelastic EV demand curve with less demand compared to the previous charging figures due to the influence of higher prices on charging station selection. Lower demand at the charging station indicates the timings for energy turn up and energy turn down are shorter. Therefore, Figure 3.12 shows more charging happens outside the peak and off peak timings compared to figures 3.8 - 3.11 where there are longer periods for balancing services. EVs aim to charge before the energy turn down period if possible to discharge power at high prices when the charging station provides energy turn down services. Compared to previous graphs where EV profiles during energy turn down period were positive with fast charging 2 and rapid charging ratings during one hour, EV profiles in Figure 3.12 show negative bidding is feasible for the whole energy turn down period (two consecutive hours). However more positive charging occurs outside energy turn up period as the timings of this period are not sufficient for charging most EVs to meet EV trip requirements. Capacity bidding with the more inelastic demand curve case is less than the capacity bidding in the cases where there are more EVs arriving at the charging station with an original and more elastic EV user type demand curve. The reason for this is fewer EV arrivals and fewer hours for making energy exchange for energy turn up and turn down periods in the more inelastic demand curve case in Figure 3.12.

Figure 3.13 shows the charging profile of the last case of evaluation, unidirectional charging with a more inelastic EV demand. Similar to the V2G case, more charging happens outside energy balancing services timings and specially for the case of fast charging 1 rating. Compared with unidirectional charging with the more elastic curve, it can be observed in the results in Figure 3.13 that trip requirements are met without the need to charge during turn down period which is when prices are more expensive. The results of total bidding capacity is most limited in the more inelastic demand curve case in Figure 3.13 where there are less EVs available for charging and less energy turn up periods compared to other cases with different demand curves. An appreciation of the final revenues, costs and utilities could provide more insights about the trade-offs between timing of balancing periods and flexibility capabilities of EVs considering limits for charging to meet trip requirements.

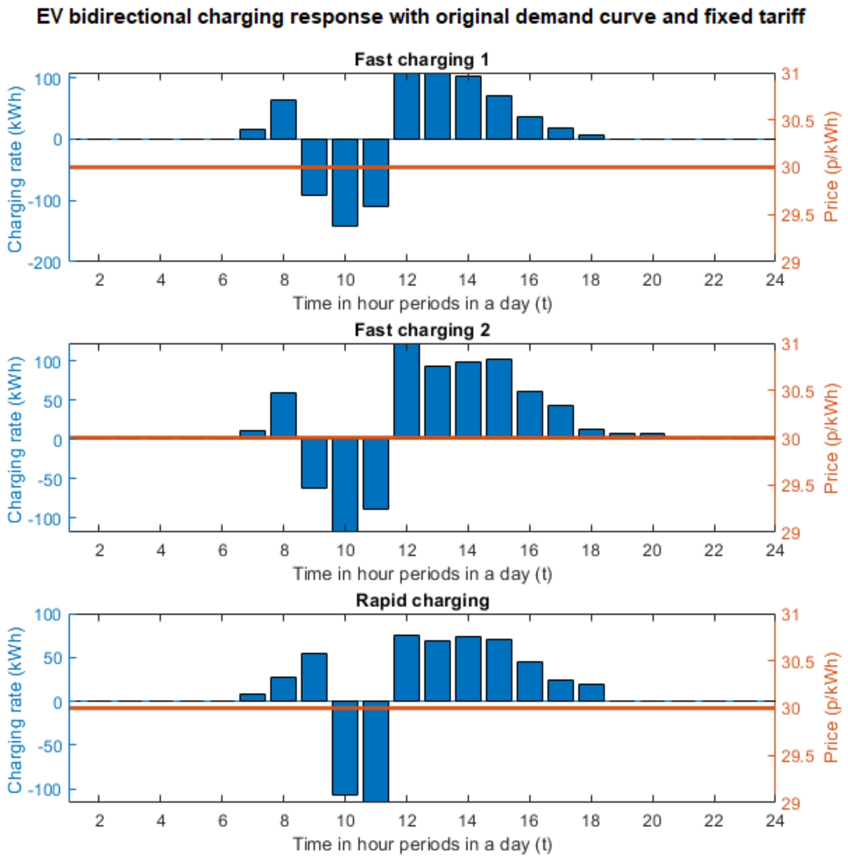


Figure 3.14: EV charging profiles as a response to fixed prices with original demand curve using different charging type cases and bidirectional capability.

In order to compare the bi-level optimisation model proposed in this thesis, a simple fixed tariff of 30 p/kWh is used to compare bidding capacity in figure 3.14. This is the closest comparison to existing research work where a fixed tariff is used to influence driver behaviour to participate in balancing services. It is important to mention that flexibility has been used to maximise revenues of the charging station and not EVs necessarily, which is not convenient for EV users and the charging station ends up taking advantage of charging and pricing as in the work of Sortomme *et al.* [79]. The profiles were created using the data inputs from the original demand curve with V2G technology. The results show almost lack of influence over EV charging profiles for energy turn up periods, where charging happens only to meet trip requirements subject to departures. Overall capacity bidding is smaller compared to Figure 3.8 as a result of EV users not influenced to discharge and then charge as much energy as possible with a tariff difference. To conclude, it can be observed in Figure 3.14 that EV charging has been modelled given a fixed tariff, which does not provide a significant influence over charging of EV users in order to both charge EVs and bid energy into auction balancing service markets.

### 3.3.4 Revenues, Costs and Utilities

Moving on with the results of this section, let's continue with the analysis of utilities, revenues and costs obtained from pricing and EV charging profiles. Figure 3.15 shows percentages of costs and revenues with V2G (bidirectional) technology at different charging ratings (fast charging 1, fast charging 2 and rapid charging from top to bottom), and three inverse demand curves. Revenues come from energy turn down, energy turn up and EV charging, while costs come from energy paid to EVs (energy turn down periods only) and energy purchase from the grid. The biggest revenue from all cases comes from energy turn down followed by EV charging and energy turn up, except for the fast charging 1 with the original demand case where revenue sources from energy turn up are greater than EV charging. The biggest costs for all cases comes from energy paid of EV drivers for V2G provision. Overall cost percentages increase when demand is more elastic and decrease with a more inelastic demand. In contrast, percentage of overall revenues are greatest with the more inelastic demand curve of EVs followed by the original demand curve and then the more elastic curve, except for the rapid charging case where overall revenues are slightly higher in percentage with the more elastic curve than with the more inelastic curve. This difference in percentages of costs and revenues from Figure 3.15 can be attributed to pricing strategies at varied demand elasticity and expected demand at the charging station.

Revenues and costs from G2V (unidirectional) technology at different charging rat-

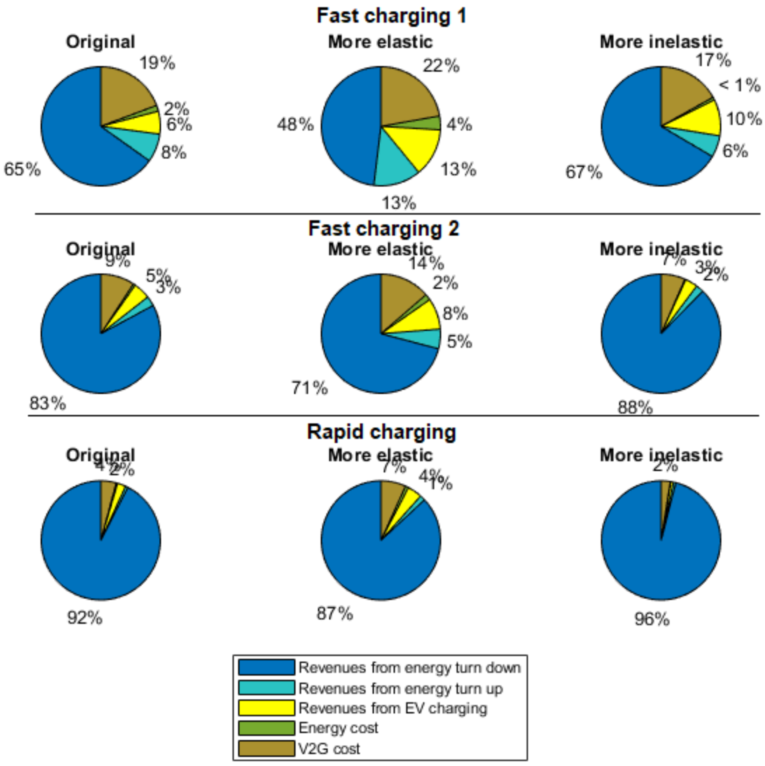


Figure 3.15: Potential revenues and costs from different charging type cases with pricing strategies using different inverse demand curves and bidirectional capability.

ings (fast charging 1, fast charging 2 and rapid charging from top to bottom) and demand elasticity are illustrated in Figure 3.16. In comparison with V2G revenues, G2V biggest revenue source is energy turn up for all the cases. Costs come only from energy grid costs and it is the smallest percentage in all pie charts. Similar to costs and revenues of V2G technology, the percentage of revenues increases with a more inelastic demand and decrease with a more elastic demand. Percentage of costs increase with a more elastic demand and decrease with a more inelastic demand. These different changes in revenues and costs can be attributed to the pricing strategies established with each variation of inverse demand curves. That is, when there is more elasticity of demand, prices are lowered so that more EV customers could be influenced to arrive at the charging station and thus cost total percentage increases as there are less utilities associated to the operation of the charging station. Likewise, when demand is more inelastic there could be fewer customers arriving at the charging station but they are willing to pay a high price for charging, thus

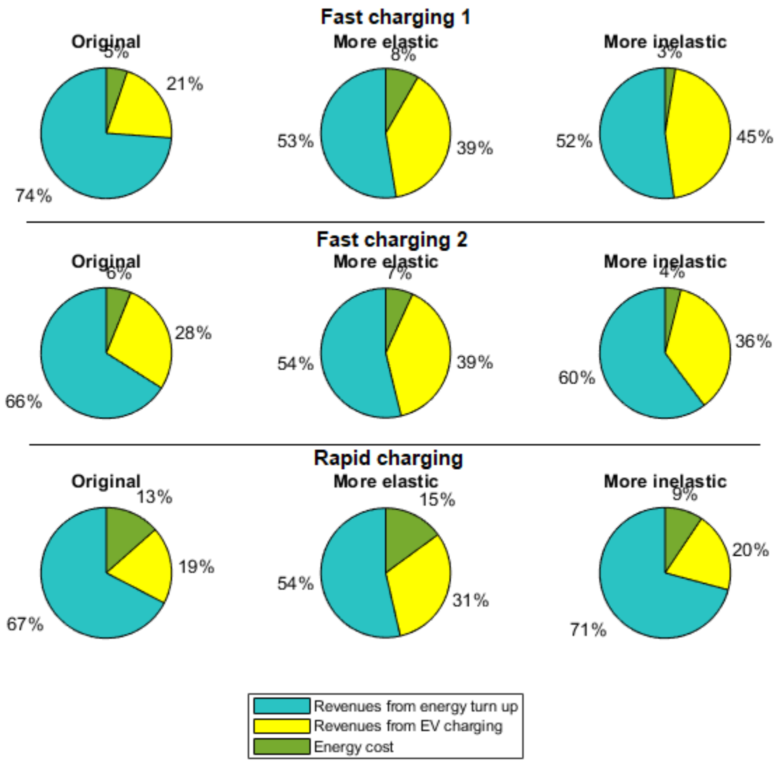


Figure 3.16: Potential revenues and costs from different charging type cases with pricing strategies using different inverse demand curves and unidirectional capability.

there are less total percentage costs and there are more utilities associated to the operation of the charging station.

Having described costs and revenues in previous paragraphs, total utilities or net profits in Figure 3.17 provide values in pounds (£) for a better comparison between all cases. The V2G or bidirectional cases with the more inelastic curve are the most profitable cases, and specifically the case of rapid charging is more profitable than the other charging ratings, this could be a result of the use of increasing prices and overall greater bidding capacity to offer for balancing services compared to the other charging ratings. The V2G case with the original demand curve represents the second place in terms utilities and the case with the more elastic curve is third place. Similar to the V2G cases, G2V or unidirectional cases with greater net profits come from the more inelastic curve for the charging ratings of fast charging 1 and 2, however for the case of rapid charging rating the most profitable case is the original curve. The differences between revenues is more notorious in the V2G cases

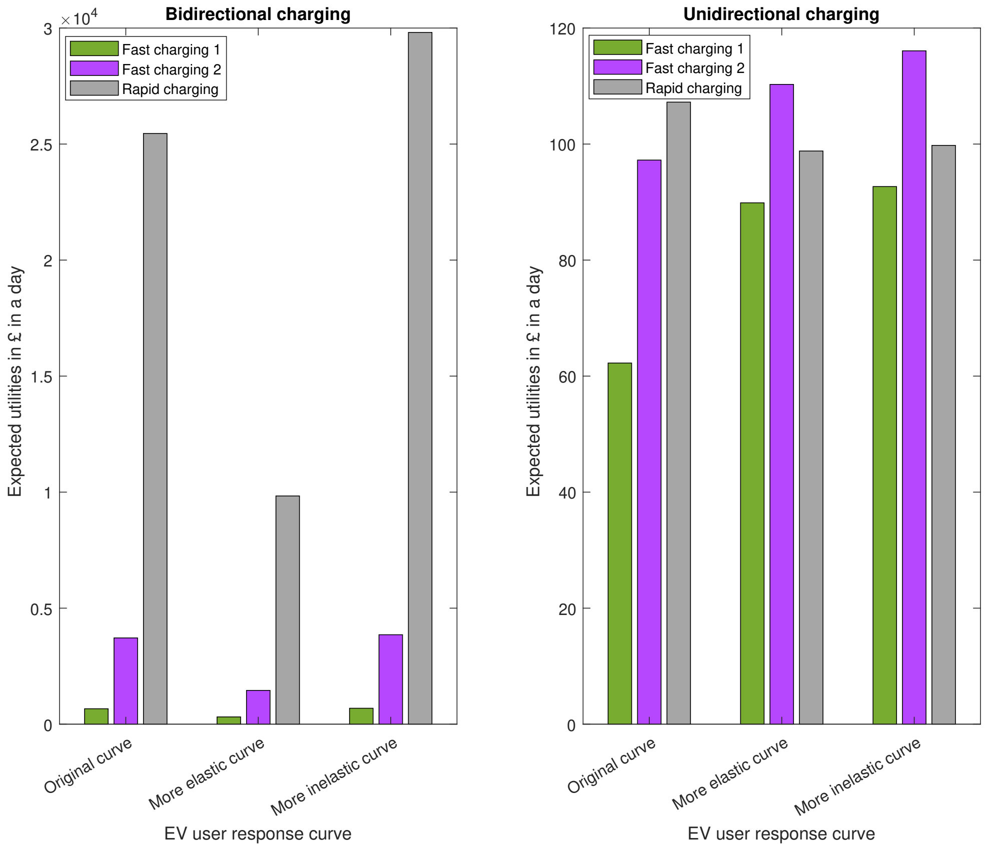


Figure 3.17: Net profits with pricing using the three inverse demand curves and charging cases.

than in the G2V cases, such differences suggest higher prices of energy turn down provide greater revenues. Also, the symmetric pricing structure used for both selling energy for EV charging and buying energy from EVs, suggests that to balance the high prices paid to EV users when discharging energy back to the grid, in the V2G technology cases, additional revenue streams when bidding energy into balancing services should also be high. It is assumed however that energy markets for instance balancing services of National Grid accept the proposed bidding at the capacity, price and time specified from the EV charging station operator. The pricing strategies for demand response show the potential for V2G and G2V technologies, nevertheless diverse route to market strategies such as a mix of bidding options into balancing services market, wholesale market, distribution markets is out of scope of the work in this Thesis. To provide additional clarity on the numbers presented in the Figures in this Section, a detailed graph with breakdown of utilities that include stacked numbers of revenues and costs is included in Figure 7 as an Appendix.

## 3.4 Chapter Remarks

### 3.4.1 Discussion

The dynamic time of use dynamic pricing strategies proposed demonstrated that EVs can be influenced to provide balancing service provision. These tariffs are a contribution to the current pricing strategies which can be used for congestion minimization or as peak shaving mechanisms in the area of EV pricing. The usage of an inverse demand curve (demand and price) demonstrated how prices can be optimised to maximise revenues as a learning approach to improve previous settings of prices during a day. Net profits for the charging station operator have the highest potential in the case of V2G technology with fast charging where net profits can be up to £29810 in a day. Then, the EV charging control determined the bidding capacity during balancing service timings accurately. It quantified stochastic driver behavior and modeled the charging schedules appropriately with different charging speed ratings, unidirectional (G2V) and bidirectional (V2G) technology. The constructed bi-level optimisation approach, firstly for pricing and secondly for EV charging bidding and control, showed these two considerations are great complements for the operation of a low carbon charging station. An evaluation of the model with stochastic variables and different technology provided design insights about the potential of each case participating in balancing services.

Positive revenues are obtained from all cases evaluated in the results section, this means the pricing strategies can adequately manage to create economically feasible operations of a low carbon (solar) charging station station with participation in balancing or ancillary services using different charging technology. V2G technology was the best strategy in terms of hourly bidding capacity with a maximum of 776 kW for regulation down and 680 776 kW for regulation up. However, the proposed model assumes a charging station can establish prices from a monopoly perspective and responses to competitive pricing with another charging station around the area is not considered. Competition from the auction market side of National Grid, for example where other bidders can offer lower prices, is also not considered. These two barriers can be tackled with addition of competitive variables when setting prices to provide a more dynamic setting before going into the market successfully. Competition for EV charging is a relatively unexplored area. Future additions to the bi-level optimisation proposed in this paper that could provide more competitive and realistic pricing strategies operating in the market also include research in improved timings to maximise EV flexibility.

### 3.4.2 Conclusion

In this chapter, a bi-level optimisation was proposed for pricing and for aggregating energy bidding of a low carbon charging station participating in balancing services. First, pricing strategies were developed for energy bidding to enter in National Grid auctions and for generating a desirable charging response from EV drivers. EV charging prices were created to promote charging during energy turn up timings and to promote discharging during energy turn down timings. Second, an EV charging optimisation control determined the charging schedules with bidding quantities during balancing services periods. Both algorithms worked together to announce bids and prices in a day ahead strategy given historical information to the operation of the charging station such as: quantity responses to price, PV power forecasting, stochastic variables of EVs (arrivals, departures, trip requirements, state of charge) and charging rate limits from both the charging station and EVs.

Directions for future research using the model proposed in this Chapter include improvements for the pricing and EV charging algorithms. The model proposed can be further developed to include more goals in the objective function and to be used in another markets such as carbon markets. These two considerations are addressed in the following Chapter of this thesis. Other improvements out of scope of this thesis) could be related to Updates to the pricing algorithm can consider competition impact on revenues for example when EVs know price comparison for charging station before arriving to a specific charging station. Competitive additions can also add variation in price strategies as responses to changes in prices from other charging station. The fundamentals of the pricing algorithm can also be used to create new tariffs that are specific to a balancing service type. Also, differences in demand curves could be explored further to create tariffs for differentiated customers with more elastic or more inelastic demand responses. In terms of extensions to the EV charging control, additional considerations can include aggregated charging restrictions to meet grid requirements, voltage, reactive power and frequency standards set by the network operator.

# Chapter 4

# Multi-objective EV Charging Optimisation

## 4.1 Introduction

A smart charging optimisation was proposed in Chapter 3 to model EV charging schedules where EV drivers benefit from real time pricing schemes controlled by a charging station operator that uses EV battery capacity to support the grid with balancing services. However, this bi-level EV charging optimisation, did not consider applicability of the model to be used in other energy markets. Also, the EV charging optimisation was formulated with a single objective function to minimise EV bills, however, other considerations for the model could include stakeholders involved whose interests could be conflicting. To continue with research about smart charging schemes for EVs, a multi-objective genetic algorithm is proposed in this Chapter to analize the potential of EV charging to reduce carbon emissions. Fairness between all the objectives involved is evaluated, and different technology for EV charging is compared. To evaluate trade-offs, different weights to the goals in the multi-objective function are presented and discussed.

The research in this Chapter offers solutions and analysis to tackle ***Objective 3*** and ***Objective 4*** which were stated in the Introduction section of this thesis.

***Objective 3*** is to design a control scheme for EV charging to reduce carbon emissions. The contributions presented in this Chapter related to this objective are: new formulation of smart EV charging to reduce carbon emissions that includes goal of EV users, charging operator and carbon regulator, weights are assigned to each goal as design optimisation variables. ***Objective 4*** is to design a multi-objective optimisation approach to ensure fairness between all objectives and evaluate the trade-offs between all stakeholders. To address this goal, this Chapter presents the following contributions: linear programming formulation integration with genetic algorithm to ensure fairness and reduction of carbon emissions. For this integration, two non-dominated criteria is proposed: best ranked solution and minimisation of carbon emissions.

This Chapter proposes a multi-objective genetic algorithm for a charging station operator to ensure fairness and reduction of carbon emissions. Specific contributions of are defined as follows:

1. New multi-objective optimisation for EV charging with inclusive goals focuses on reduction of $CO_2$eq emissions that include conflicting interests of EV users, charging station operator and a carbon regulator. The formulation includes time dependent weights of each objective and complex restrictions. The formulation also includes new measurement of $CO_2$eq emissions stored in EV batteries to keep a carbon allowance limit as a restriction of EV charging scheduling. In addition, pricing in real time considers carbon tax depending on intensity of electricity carbon factor in the UK that provides insights about efficiency of such taxes to reduce $CO_2$ emissions when charging EVs.

2. An integrated multi-objective optimisation with a genetic sorting algorithm is proposed, where weights of each objective function are used as design variables to adequately search non-dominated solutions. This new method combines NSGA-II search algorithm to ensure fairness of the proposed multi-objective formulation of EV charging to reduce $CO_2$eq emissions. Two new selection

criteria for ensuring fairness and reductions of $CO_2$eq emissions are proposed as strategies to select optimal solutions from a pareto frontier.

3. Flexibility charging of EV users at different parking locations and using different EV charging technology is explored in order to examine the best results for reduction of $CO_2$eq emissions. Overall trade-offs are studied using key performance indicators such as $CO_2$eq emissions and revenues/costs coming from EV charging schedules. Limitation of the search model and recommendations are stated to support transition to a decarbonised commercial vehicle sector.

Details of the proposed multi-objective formulation are presented in section 4.2 followed by the methodology to ensure fairness and carbon reductions in section 4.3. Then section 4.4 evaluates the system model based on trade-off comparison of the different goals, fairness and carbon savings potentials for different cases, which include EV charging at residential and work location and different charging technology restrictions. Finally, section 4.5 provides discussions about the obtained results and conclusions.

## 4.2 Problem Formulation

The multi-objective optimisation model proposed in this Chapter is based on the model proposed in Chapter 3 and it can also be used for various applications where a commercial aggregator could operate EV charging stations, for instance in parking lots where EV users go to work or in off-street parking spaces in residential areas near the homes of EV users. Figure 4.1 illustrates the multi-objective formulation proposed in this Chapter, it presents the stakeholders involved, their main activities, inputs and outputs required for the model. The charging station operator represents the EV aggregator or charging station operator that is able to sell/buy energy to EV users and bid energy into carbon trading markets. First, the charging station operator resolves the economic dilemma of establishing energy prices (that EV users

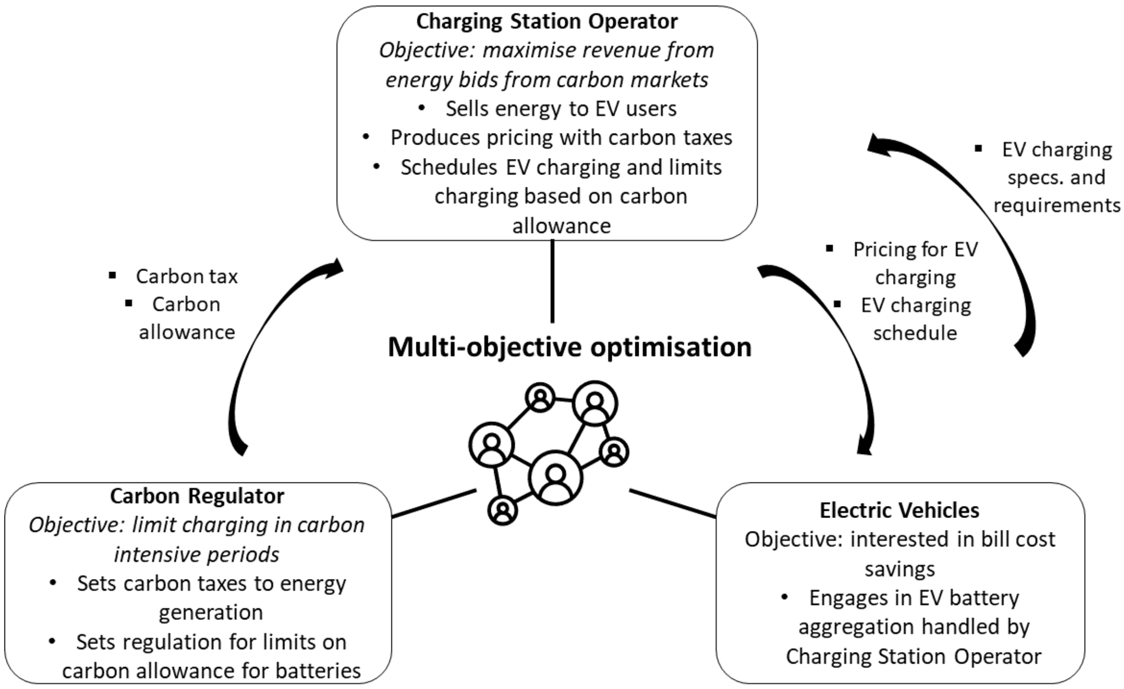


Figure 4.1: Multi-objective optimisation with conflicting objectives, activities and information flow of inputs and outputs.

will pay) and carbon trading prices (to be paid to the charging station operator). Then, EV charging scheduling is obtained from a multi-objective optimisation. The multi-objective goals consider a charging station operator, a carbon regulator and electric vehicles. The charging station operator aims to obtain an additional revenue stream to EV charging with provision of energy to carbon markets during high intensive carbon grid periods. The virtual carbon regulator aims to encourage EV charging during low intensive carbon periods with a reference to a projected nominal value to support transition to renewable generation. EVs' aim is to minimise the energy costs they will have to pay for charging, and to sell energy to the charging station operator with V2G technology if revenues are an option after EVs participate in energy arbitrage. To evaluate the applicability and limits of the multi-objective optimisation, V2G and G2V technology are compared in two charging locations to analyze the potential of EV charging schemes to minimise $CO_2$eq emissions as much as possible.

EV availability and carbon intensity levels are studied in order to match EV charging strategies following electricity grid carbon factor signals for two charging locations.

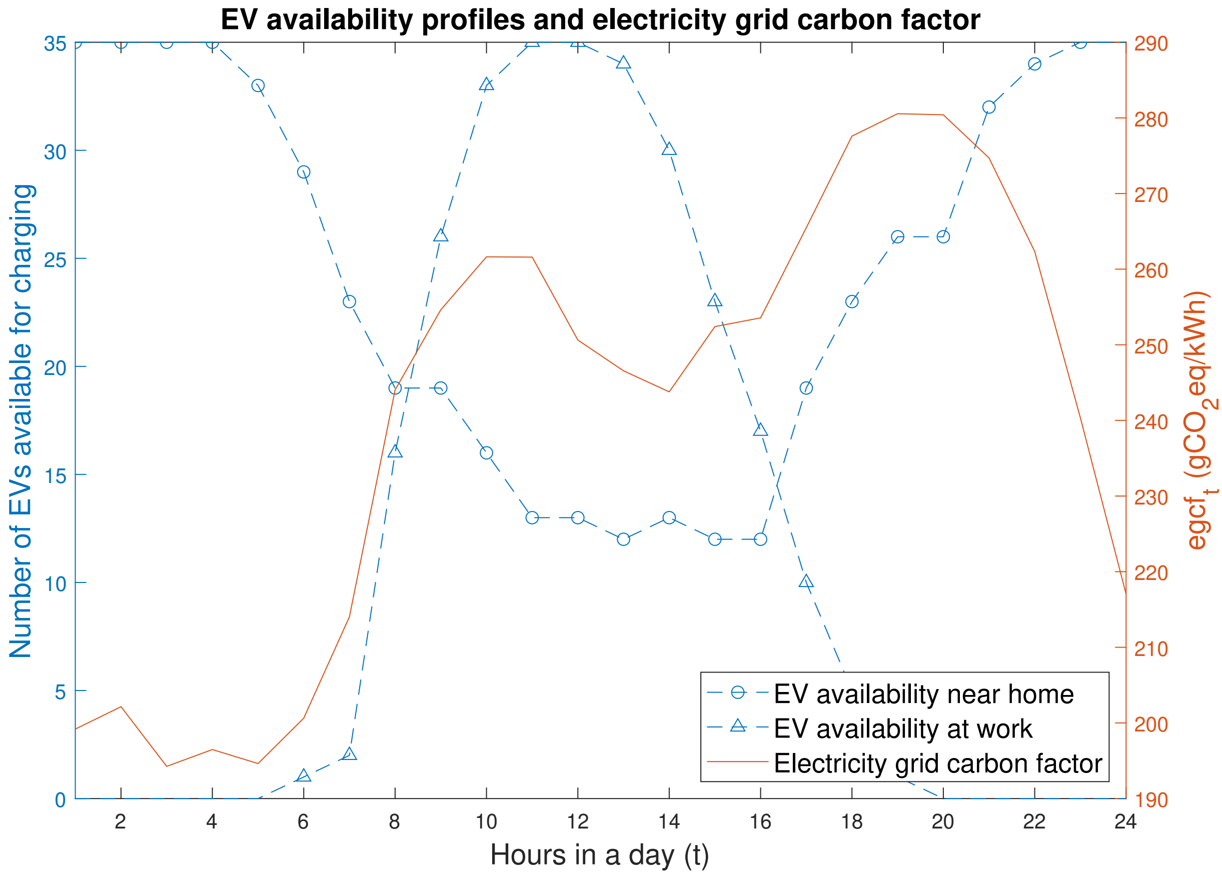


Figure 4.2: Electricity grid carbon factor and EV availability at work and residential locations during a day.

Figure 4.2 shows the variation of independent EV availability during a day for both charging at work and near home locations with stochastic driver behavior of 35 EVs, which is obtained with the sum of stochastic individual availability from equation 3.2.5. This Figure also shows carbon intensity levels in the grid depending on an average sample from UK energy mix every hour in a day. EV charging at low intensive periods can happen during late hours of night and early hours in the morning. Higher carbon intensive periods happen in mid morning and in the evening. These timings of high carbon intensity can be used for trading energy from EVs into carbon markets when discharging EV energy back to the grid. Charging recovery from discharging periods can happen when intensity levels of carbon are low based on EV availability restrictions to meet driver requirements. Thus, the capacity for reduction of carbon emissions with EV charging is formulated using electricity grid carbon signals with 3 objective functions. The computation of EV scheduling depends on the weights of each goal of the multi-objective formulation, and on EV charging requirements such as availability at each location, trip, initial state of charge and also depends on EV charging technology such as V2G, G2V. Specific details about the problem formulation and selection of optimal solutions are presented in the following two Chapters.

### 4.2.1 The Role of the Regulator

Measurements for $CO_2$eq emissions are used as inputs for the carbon regulator's goal. These measurements have been estimated by taking into account type of generation by fuel type ($m \in M$) and their equivalent $CO_2$eq emissions per unit of energy generation mix [150]. Thus, the hourly electricity grid carbon factor ($egcf_t$) is obtained from the equivalent $CO_2$eq emissions in the generation mix with the sum of carbon factor per fuel type ($cr_{m,t}$) per energy generation by fuel type ($e_{m,t}$) over the total generation for every hour during a day as follows,

$$egcf_t = \sum_{m=1}^{M} cr_{m,t} \cdot e_{m,t} / \sum_{m=1}^{M} e_{m,t}, \tag{4.2.1}$$

where carbon factor per fuel type estimates for renewable and non renewable sources of energy are can be computed from the values in Table 4.1 obtained from [151].

The carbon regulator goal is to encourage charging when it is more convenient for the environment in terms or carbon emissions. Therefore, similar to the work in [46] the regulator aims to limit charging during carbon intensive periods, which can be achieved by coordinating EV charging with the electricity grid carbon factor described in the previous paragraph. This factor is used to measure carbon changes based on a carbon factor target in the grid ($egcf_a$), where values above the carbon factor target receive zero encouragement in order to limit EV charging in the objective function. Thus, to estimate any values that do not meet the recommended carbon

Table 4.1: Median carbon factor in $CO_2$eq/kWh

| Fuel type | Carbon factor |
|---|---|
| Coal | 820 |
| Gas | 490 |
| Biomass | 230 |
| Solar PV (Utilty Scale) | 48 |
| Solar PV (Rooftop) | 41 |
| Hydropower | 24 |
| Wind (Onshore) | 12 |
| Wind (Offshore) | 12 |
| Imports (France) | 12 |
| Imports (Netherlands) | 483 |
| Imports (Ireland) | 431 |
| Imports (Belgium) | 230 |
| Imports (Norway) | 12 |
| Storage | 24 |

target, $f_t$ estimates the variations accordingly by,

$$f_t = egcf_t/egcf_a. \tag{4.2.2}$$

The proposed goal of the carbon regulator ($Re_t$) receives a negative value when the electricity carbon factor is above the carbon target when computing $1 - f_t$ times the optimised EV charging rate $q_{i,t}$, and receives the value of 0 when the electricity carbon factor is under the limits of the carbon target. Therefore, the objective function of the carbon regulator is to maximise EV charging during carbon factor timings below the carbon target and to not encourage charging at any other timings above the carbon target for the whole set of EVs ($I$), from EV arrival ($ar$) to departure ($de$) times at the charging station. The objective of the carbon regulator is defined by,

$$\underset{q_{i,t}}{\text{Max}}\ Re(q_{i,t}, f_t) = \begin{cases} \sum_{i=1}^{I} \left\{ \sum_{t=ar}^{de} q_{i,t} \cdot (1 - f_t) \right\}, & \text{if } f_t > 1 \\ 0, & \text{otherwise.} \end{cases} \tag{4.2.3}$$

### 4.2.2 The Role of the Charging Station

Emerging markets such as carbon markets provide opportunities to use demand side management resources for flexibility and carbon reduction purposes. The management of EV charging brings the possibility to handle EV batteries as an aggregated virtual battery in different time slots. Here, the charging station acts as an EV aggregator that can use flexibility capabilities to bid energy into carbon markets with the use of V2G or bidirectional technology. However, EV batteries can still have carbon impacts because they are ultimately charged with the carbon footprint from the energy available in the grid. Consequently, the charging station aims to generate an additional revenue stream with participation in carbon markets from managing discharged power from EV batteries while meeting a carbon emission storage target constraint imposed by a carbon regulator. This target is similar to the carbon target imposed to the grid in the regulator objective function but applied to EV battery charging carbon footprint.

To estimate the carbon factor stored in EV batteries in a time frame, a carbon factor for each EV is estimated ($evcf_{i,t}$). When the EV arrives at the charging station, it is expected that there is already a metered carbon factor of previous charging sessions. Thus, the EV carbon factor in hour 1 is estimated by,

$$evcf_{i,1} = soc_{i,0} \cdot cf_{i,0} + q^{+}_{i,1} \cdot egcf_1 + q^{-}_{i,1} \cdot cf_{i,0}, \tag{4.2.4}$$

where $cf_{i,0}$ is the carbon factor equivalence to the state of charge $soc_{i,0}$ when an EV arrives at the charging station. At the end of the first hour period after arrival at the charging station, carbon emissions from charging or discharging are computed. When the charging rate is positive ($q^{+}_{i,1}$) the corresponding charging emissions come from the grid. When the charging rate is negative ($q^{-}_{i,1}$), equivalent $CO_2$ emissions come from the carbon factor of the EV from previous charging sessions.

In the following hours of the charging schedule, the stored EV carbon factor is estimated by,

$$evcf_{i,t} = evcf_{i,t-1} + q^{+}_{i,t} \cdot egcf_t + q^{-}_{i,t} \cdot evcf_{t-1}, \tag{4.2.5}$$

where, $CO_2$ emissions are carried out from the previous hour and remaining carbon emissions are estimated from the charging schedule and corresponding carbon emissions from the grid.

As mentioned in this subsection, the charging station is restricted by a carbon target requirement coming from the carbon emissions related to EV charging. Thus, to be able to discharge energy back to the grid and participate in carbon markets, the following carbon footprint restriction must be satisfied,

$$evcf_{i,t} \leq ca_{i,t}, \tag{4.2.6}$$

where the $evcf_{i,t}$ must be less than or equal an estimated carbon allowance per EV $(ca_{i,t})$. The charging station operator will be able to obtain revenues if EVs discharge energy back to the grid and if EV batteries meet the carbon footprint limit. Thus, the revenues from participating in carbon markets are defined by,

$$\underset{q_{i,t}}{\text{Min}}\ CS(pm_t, q_{i,t}) = \begin{cases} \sum_{i=1}^{I} \left\{ \sum_{t=ti}^{tf} pm_t \cdot q^{-}_{i,t} \right\}, & \text{if } q_{i,t} < 0 \\ 0, & \text{otherwise,} \end{cases} \tag{4.2.7}$$

where the charging station denotes a carbon price for selling energy from EV users in carbon markets $pm_t$, and it receives revenues if the EV can discharge energy back to the grid. Note that the objective function is to minimize carbon price times a negative charging rate which means the charging station receives revenues when the value of the objective function $CS_{i,t}$ is negative during specific timings established by the charging station operator from $ti$ to $tf$.

### 4.2.3 Pricing with Carbon Tax

The pricing dilemma for setting carbon prices (for carbon markets) and for setting prices for selling energy for EV charging is estimated using the data driven pricing algorithm developed in Chapter 3, section 3.2.1, the reader can go back to the details of the algorithm for more information. For practical purposes, only additions to the algorithm are explained. Thus, the pricing mechanism is defined by the charging station operator which announces prices that are computed from maximising revenues using historical EV user response to price and costs. The difference between the pricing scheme in section 3.2.1 and the one in this Chapter, is that a carbon tax is included in charging station operator's costs. Thus, the cost to buy energy from the grid ($cg_t$) is estimated by adding a carbon tax every hour ($ctax_t$) based on electricity grid carbon factor by,

$$cg_t = cg_t + egcf_t \cdot ctax_t. \tag{4.2.8}$$

Similar to the pricing algorithm for balancing services, pricing for regulation down estimates are comparable to bidding energy into carbon markets. The estimation for regulation up (increase charging rate of EV) is not considered as there isn't a carbon trading mechanism for just increasing charging rate. Thus, pricing for selling and buying energy to/from EVs is estimated by,

$$pf = \begin{bmatrix} p_1^* & \dots & p_{ti-1}^* & pc_{ti} & \dots & pc_{tf} & p_{tf+1}^* & \dots & p_{24}^* \end{bmatrix} \tag{4.2.9}$$

where $pf$ is the pricing matrix in a day, it includes the optimum pricing mechanism for selling energy to EVs ($p^*$), and the pricing for buying energy from EVs ($pc_t$).

Timings for setting up either an optimum price or a price for buying energy from EVs in carbon markets for equation 4.2.9, are estimated considering the electricity grid carbon factor and number of EVs available to provide energy back to the grid. Timings for allowing EVs to discharge energy are estimated when measuring carbon grid intensity with classifications of high, medium and low levels ($h_t, m_t,$ and $l_t$) as follows,

$$(egcf_u - egcf_l) \cdot \frac{2}{3} \leq h_t \leq (egcf_u - egcf_l), \tag{4.2.10}$$

$$(egcf_u - egcf_l) \cdot \frac{1}{3} \leq m_t < (egcf_u - egcf_l) \cdot \frac{2}{3}, \tag{4.2.11}$$

$$(egcf_u - egcf_l) \cdot 0.01 \leq l_t < (egcf_u - egcf_l) \cdot \frac{1}{3}, \tag{4.2.12}$$

where carbon intensity levels are defined by lower ($egcf_l$) and upper limits ($egcf_u$) of the electricity grid carbon factor in a day by,

$$egcf_l = min(egcf_t), \tag{4.2.13}$$

$$egcf_u = max(egcf_t). \tag{4.2.14}$$

Only the periods where there is high carbon intensity and high capacity of EVs at the charging station, as defined in section 3.2.1, are considered for estimating the initial ($ti$) and final time ($tf$) to allow EV energy discharging and buying of electricity. Carbon pricing $pm_t$, which includes expected utility $\delta$ of the charging station operator, for selling energy from EVs into carbon markets is estimated with the equation to bid regulation down energy in balancing services as stated also in section 3.2.1, defined by,

$$pm_t = \begin{cases} ((u_t(Q_t^*) + pd_t \cdot |Qd_t|)/(|Qd_t|)) & \\ \cdot(1+\delta), & \text{if } Q_{i,t} \leq 0 \\ ((u_t(Q_t^*) + cg_t \cdot (Qd_t - (Ps_t \cdot \mathrm{n}))) & \\ /(Qd_t)) \cdot (1+\delta), & \text{otherwise.} \end{cases} \tag{4.2.15}$$

### 4.2.4 The Role of EV drivers

EV drivers have the potential to allow a charging station to discharge and charge energy to meet trip requirements according to the restrictions of charging rate and battery capacity. Therefore, the goal of EV drivers is to use their availability at the charging station as a flexibility advantage to charge energy when it is cheap and sell energy if possible to minimise energy costs and even obtain revenues. The goal of EV drivers is defined by,

$$\underset{q_{i,t}}{\text{Min}}\ EV(q_{i,t}) = \sum_{i}^{I} \left\{ \sum_{t=ar}^{de} pf \cdot q_{i,t} \right\}, \tag{4.2.16}$$

where $q_{i,t}$ is the charging rate at each our to pay for with pricing scheme $pf$. Restrictions such as trip requirements, battery capacity and carbon allowance are considered in the final optimisation formulation with the multi-objective perspectives of the charging station, regulator and EV drivers.

## 4.3 Multi-objective Formulation

The roles described in subsections 4.2.1-3 are formulated in a multi-objective formulation in this section. For this purpose, a weighted sum of all objectives is formulated as a single objective formulation as part of multi-objective genetic algorithm. Weights of individual objectives are explored and compared to establish fairness and to select optimal solutions based on two different criteria to ensure overall preference maximisation and to reduce carbon emissions. The multi-objective formulation is a combination of the goals of the regulator, charging station operator and EV users. To integrate all goals in an objective function, they are adapted to work with a minimisation function defined as follows,

$$\underset{q_{i,t}}{\text{Min}}\ \alpha \cdot \frac{EV(q_{i,t})}{EV_{max}} - \beta \cdot \frac{R(q_{i,t}, f_t)}{R_{max}} + \gamma \cdot \frac{CS(pm_t, q_{i,t})}{CS_{max}}, \tag{4.3.1}$$

where $CS_{max}$, $R_{max}$ and $EV_{max}$ are the maximum values of the charging station operator, regulator and EV drivers respectively, considering maximum stochastic dynamics of all variables affecting each goal combined with maximum charging rate that could be used to charge an EV in a day. These maximum values are used to normalise each objective function, a practical approach for dimensional purposes. Then weights $\alpha$, $\beta$, and $\gamma$ are added to each normalised objective to obtain different optimal solutions. In addition, individual weights are restricted to percentage values between 0 to 1 and the sum of weights $\alpha+\beta+\gamma$ is restricted to 1 to guarantee exploration of inclusive solutions. The selection of weights to assign to each solution are selected based on randomised generation of weights that meet the previously mentioned requirements, then the selection of weights are evaluated based on specific criteria, this proposed method is described in the following paragraphs.

The multi-objective formulation proposed has numerous set of solutions which can be obtained based on weighting criteria. Finding the best weights for each objective function can be made from fixed-based heuristic weight criteria, nash game adapted formulations, genetic algorithms, etc. The first option could provide a simple solution to fairness for specific design objectives, however may lack application under changing dynamics of variables over time and the heuristic criteria could lack mathematical fundamentals. The second option implies a complex mathematical analysis that also could change with varying dynamics of variables over time and could loose applicability. In contrast, a genetic algorithm has the potential to evaluate different possibilities and compare the best potential combination of weights in time with any changes in variables.

A genetic algorithm such as NSGA-II proposed in [152] has the potential to search for non dominated solutions in order to find fair solutions. This algorithm has previously used for finding design variables in multi-objective optimisation as in [153] for finding the best balance between objective functions following design variables evaluated in a computational fluid dynamics simulations. Similarly, NSGA-II algorithm is used to search solutions from the multi-objective formulation proposed in this Chapter, where the weights of the multi-objective optimisation are modelled as the design variables to evaluate non-dominated solutions. In order to find the best possible combination of weights and to establish fairness between all objective functions, pareto optimality is obtained when comparing dominance between objective functions. Figure 4.3 shows the space of objective functions $f_{s,j}(\alpha_j,\ \beta_j,\gamma_j)$, $s=3$ that includes the objectives or goals of EV users, regulator and the charging station operator, as well and design variables which are the weights of the objective functions $(\alpha_j,\ \beta_j,\gamma_j)$. Dominance of the multi-objective solutions is compared between chromosomes $j \in J$ to search for fairer solutions, chromosomes and individuals are treated as the same for the research work in this thesis. A final set of non-dominated solutions forms the pareto frontier set, then two selection criteria for selection of an optimal solution from the pareto frontier is proposed.

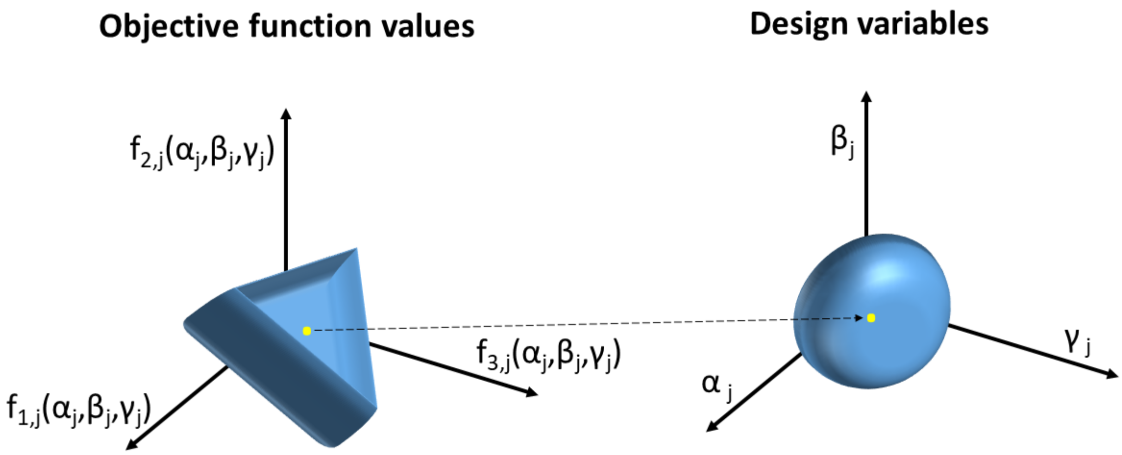


Figure 4.3: Tracking for computation of objective functions based on design variables.

The solving method of the multi-objective genetic algorithm formulation uses the concept of pareto optimality and other definitions [154; 155] which are stated below.

*Definition 1: Pareto optimality.* A solution or objective function values with weights $\alpha_j$, $\beta_j$ and $\gamma_j$ of chromosome $j$, is a pareto optimal solution if there is no other solution of chromosome $k \in J$ evaluated with weights $\alpha_k$, $\beta_k$ and $\gamma_k$, whose objective function values dominate solution in chromosome $j$ for the entire space of solutions.

*Definition 2: Dominance.* In order to ensure obtain pareto optimality, dominance between objective functions is compared. For simplicity, objective values with individual goals and weights are defined by $f_{s,j}(\alpha_j, \beta_j,\gamma_j)$. When objective functions are minimised, a solution with weights $\alpha_j$, $\beta_j$ and $\gamma_j$ dominates solution with weights

$\alpha_k$, $\beta_k$ and $\gamma_k$ when any of the following dominance conditions are satisfied. Weak dominance is represented by,

$$f_{s,j}(\alpha_j, \beta_j, \gamma_j) \leq f_{s,k}(\alpha_k, \beta_k, \gamma_k) \tag{4.3.2}$$

and dominance is represented by,

$$f_{s,j}(\alpha_j, \beta_j, \gamma_j) < f_{s,k}(\alpha_k, \beta_k, \gamma_k). \tag{4.3.3}$$

*Definition 3: Pareto frontier.* Once dominance has been established between objective functions, the non dominated solutions, that is solutions where dominance count between the objective function values is the same, are separated from the rest. Thus, the set of non dominated solutions form the pareto frontier.

*Definition 4: Pareto optimal selection.* Once a pareto frontier set is computed, it is important to select a solution to meet specific criteria. Two selection criteria is proposed in this Chapter to look for a fairest and for a greenest solution.

### 4.3.1 Pareto Frontier Evaluation

*Definitions 1-4* are used in the formulation of the multi-objective genetic algorithm proposed to evaluate solutions and select the ones that meet criteria in terms of fairness and environmental impact. The diagram in Figure 4.4 shows a visual procedure of the algorithm which is also described in the points below.

1. As a day ahead strategy, a charging station operator computes the best pricing option for EV drivers ($pf$) and for participating in carbon markets ($pm_t$) based on historical data with financial evaluation and demand response of EVs.

2. Randomised design variables are computed to evaluate the initial set of individuals in order to explore the design space so that $\alpha_j + \beta_j + \gamma_j = 1$, and each of these weights must be between 0 and 1.

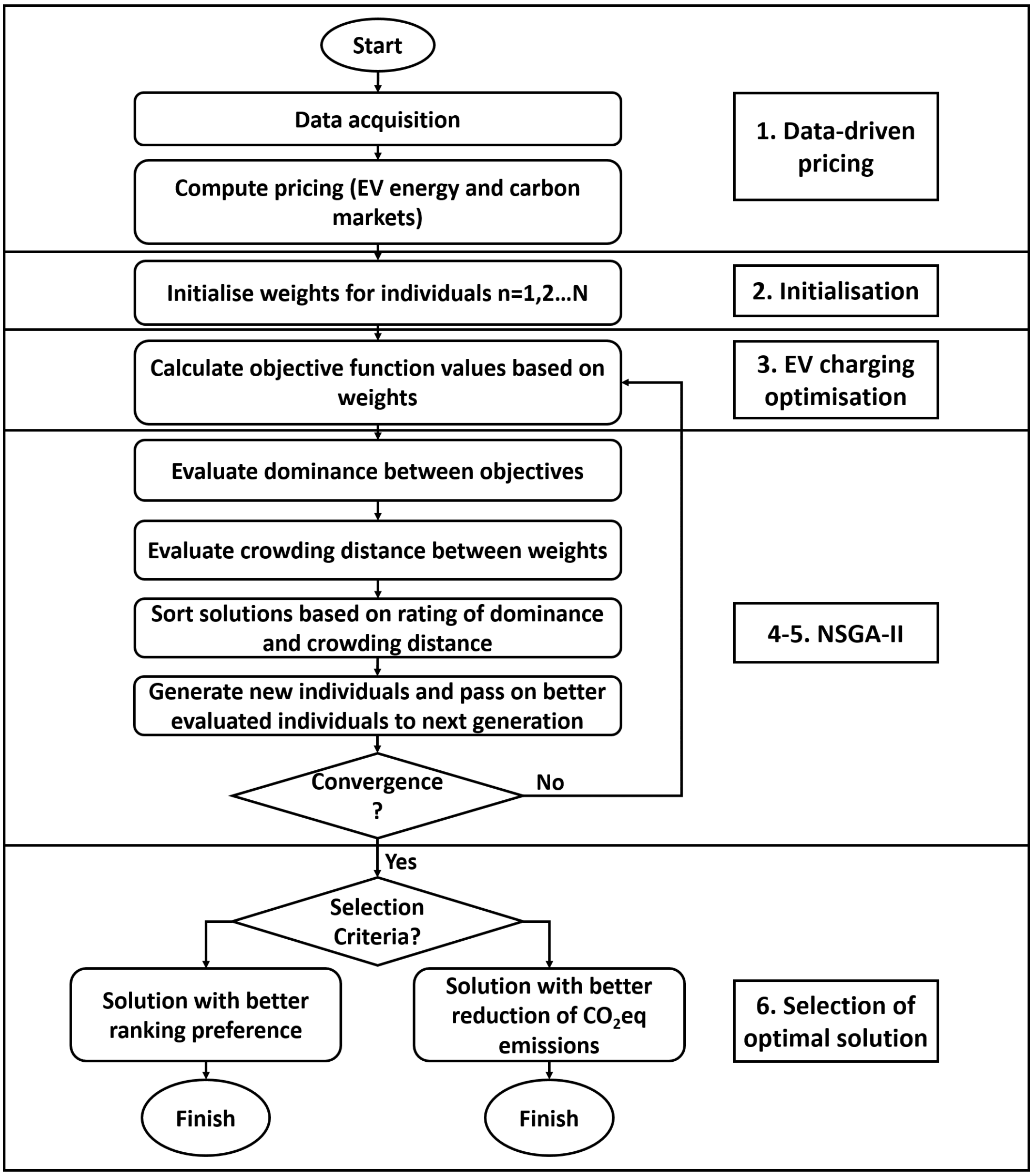


Figure 4.4: Procedure of multi-objective genetic algorithm.

3. The design variables or weights assigned to each objective function; $\alpha_j$, $\beta_j$ and $\gamma_j$, for all individuals in set $J$ is evaluated to obtain the value of each objective function value.

4. Solutions are sorted based on dominance evaluation between the individual objectives to each solution according to *definition 2*, and according to crowding distance to ensure inclusiveness of variables in the design space as proposed by Deb *et al.* [152].

5. The solutions that are better evaluated are selected for the next generation of

individuals. Also, solutions that pass on to the next generation are created form a crossover and from a mutation strategy as proposed in NSGA-II in [152].

6. Following *Definition 4*, once the pareto frontier has been obtained after running of generations, a fairest or a greenest solution is selected based on the proposed selection criteria.

### 4.3.2 Selection of Optimal Solutions

Once non-dominated solutions are obtained in a generation, convergence has been reached and the individuals in this generation form the pareto frontier. These solutions represent the options for which no objective is better off without harming each other interests. Thus, the next stage of the multi-objective optimisation is to select an optimal solution from the pareto frontier. For this purpose, two selection procedures are proposed, one ensures a preferred solution from all objectives and the second is a green solution where carbon emissions are minimised.

**Most preferred ranked solution**. Once the pareto frontier has been obtained, a preferred solution from the perspectives of EV drivers, regulator and charging station operator is obtained from a best ranked solution. The ranking assignation is based on an evaluation of a preferred distance for each individual with their respective value of the objectives as follows,

$$d_{s,j} = \frac{f_{s,j}(\alpha_j, \beta_j, \gamma_j) - fl_{s,j}}{fu_{s,j} - fl_{s,j}}, \tag{4.3.4}$$

$$fl_{s,j} = \arg\min(f_{s,j}(\alpha_j, \beta_j, \gamma_j)), \tag{4.3.5}$$

$$fu_{s,j} = \arg\max(f_{s,j}(\alpha_j, \beta_j, \gamma_j)) \tag{4.3.6}$$

where $d_{s,j}$ is the distance for each objective function $s$ and individual $j$ with relation to the best possible solution available ($fl_{s,j}$) and the maximum value from all solutions which would the worst solution ($fu_{s,j}$) within a generation. Preferred distances per objective and individual are assigned a ranking value ($r_{s,j}$) starting with 1 given to the solution with minimum distance, a value of 2 is given to the second minimum distance and so on. The sum of rankings per individual indicates the preference ranking among the three goals, therefore the overall preferred solution is the lowest ranked solution per individual defined by,

$$rp = \arg\min \sum_{j=1}^{J} r_{s,j} \tag{4.3.7}$$

where $rp$ is the solution with minimum ranking sum from the set of individuals in the pareto frontier, and $r_{s,j}$ is the ranking assigned to each individual based on preferred distance $d_{s,j}$ for each goal or objective value. This ranking can adequately manage weights of preferences in such a way that the solutions with lowest ranking can be selected. The solutions with higher ranking are penalised due to the fact that one objective could be too far from the best possible option, this way a balanced solution is obtained when the three goals have the lowest possible ranking.

**Green solution**. A green optimal solution is proposed in order to select the solution that minimises $CO_2$eq emissions from the pareto frontier. This will ensure the selection of both a non dominated solution, where comparison of weights assigned to each objective function is balanced, and a solution that is better for the environment. Thus, the selection of the green solution can be estimated by,

$$g = \arg\min \sum_{j=1}^{J} \left\{ \sum_{i=1}^{I} \Big\{ \sum_{t=1}^{T} egcf_t \cdot q_{i,t}(\alpha_j, \beta_j, \gamma_j) \Big\} \right\}, \tag{4.3.8}$$

where $g$ is the green solution with the lowest $CO_2$eq emissions based on the EV charging schedule $q_{i,t}(\alpha_j, \beta_j, \gamma_j)$ of each optimal solution from the pareto frontier, times the electricity carbon factor variation during the charging schedule for the whole set of EVs $I$.

## 4.4 Model evaluation

A formulation for EV charging has been proposed and it includes three different objectives; following the perspective of EV drivers, they aim to minimise costs for charging and also get revenues from selling back to the grid if allowed, a carbon regulator aims to maximise charging when the grid carbon intensity is less than or equal to a grid carbon intensity reference value, and the charging station operator aims to get additional revenue from participating in carbon markets. However, these three objectives vary through time, for instance EVs interests can be impacted by the dynamic real time pricing from the charging station operator, the regulator follows a carbon grid factor reference and the EV driver preferes to bid energy into carbon markets when capacity of the charging station and carbon grid factor combined are more convenient. Therefore, these objectives have conflicting interests that can lead to different solutions. The results of the multi-objective optimisation proposed in this Chapter are analyzed from the individual perspective of each objective and from the multi-objective strategies where pareto optimal solutions are compared. The results of smart charging strategies for reduction of carbon emissions are also analysed comparing scenarios for bidirectional and unidirectional charging at work and near home charging locations.

To obtain the required results for the research proposed in this Chapter, 35 stochastic EV driver profiles for home charging location are created using arrivals, departures, trip requirements and initial state of charge using with real data kindly provided by EA technology as part of "Electric Nation Project"[156]. EV driver profiles for work charging location were created in Chapter 3 with data provided also by EA technology with data sets for "Electric Avenue Project" [140], and with EV arrival and sojourn time distributions from [138], are also used in this Chapter. The empirical CDF graphs of EVs availability, trip requirements and initial state of charge for both home and work locations are presented in Figures 2-7 in the Appendix of this thesis. Electricity grid carbon factor estimations are obtained using the carbon tracker information from [151]. The reference for carbon factor of the grid ($egcf_a$) for the regulator is set as the mean value for the grid carbon factor in a day, however this could be based on governmental carbon factor targets. Table 4.2 contains all the parameters used for the simulations for this Chapter which contain some carried

Table 4.2: Simulation parameters

| Parameter | Value |
|---|---|
| Total number of EVs | 35 EVs |
| Carbon allowance ($\mathrm{ca}_{i,t}$) | 18000 $\mathrm{gCO_2eq}$ emissions |
| Carbon tax ($ctax_t$) | 18 £/$\mathrm{tonCO_2eq}$ emissions |
| Time periods in a day | 24, for every hour |
| EV arrivals (home) | Empirical CDF [156] |
| EV departures (home) | Empirical CDF [156] |
| Initial state of charge (home) | Empirical CDF [156] |
| Trip requirements (home) | Empirical CDF [156] |
| EV arrivals (work) | $ar \sim \mathcal{N}(\mu = 8,\, \sigma^2 = 1)$ [138] |
| EV sojourn time (work) | $ts \sim Logistic(\mu = 0.27,\, s = 0.06), mn = 5, mx = 18.52$ [138] |
| Initial state of charge (work) | Empirical CDF [140] |
| Trip requirements (work) | Empirical CDF [140] |
| Charging station rating | 3.7 kW [141] |
| Mitsubishi Outlander charging ratings/battery size | 3.7 and 22 kW/ 12kWh[142] |
| Nissan Leaf charging rating/battery size | 6.6 and 50 kW/40 kWh[143] |
| BMW 330e charging ratings/battery size | 3.7 kW/12 kWh[144] |
| Energy cost | 10 p/kWh [146] |
| Utility from carbon markets | 10% |

over values used in Chapter 3. The simulation for the multi-objective evaluation is done in MATLAB with Yalmip toolbox [148] as the interface to link to optimisation solver Gurobi [149]. Contrasting results of the simulations that use the parameters described are analyzed in the following section.

### 4.4.1 Trade-offs between Individual Objectives

In this section, EV charging schedules from optimisations with the three goals computed separately are obtained in order to compare EV charging schedules when following different signals form the perspectives of EV drivers, charging station operator and a carbon regulator. The main signals related to each goal are compared in order to give the reader a better understanding of the impact on EV charging rate dynamics in time. Additional graphs for comparison include the charging costs or revenues for EV drivers and the potential revenues obtained by the charging

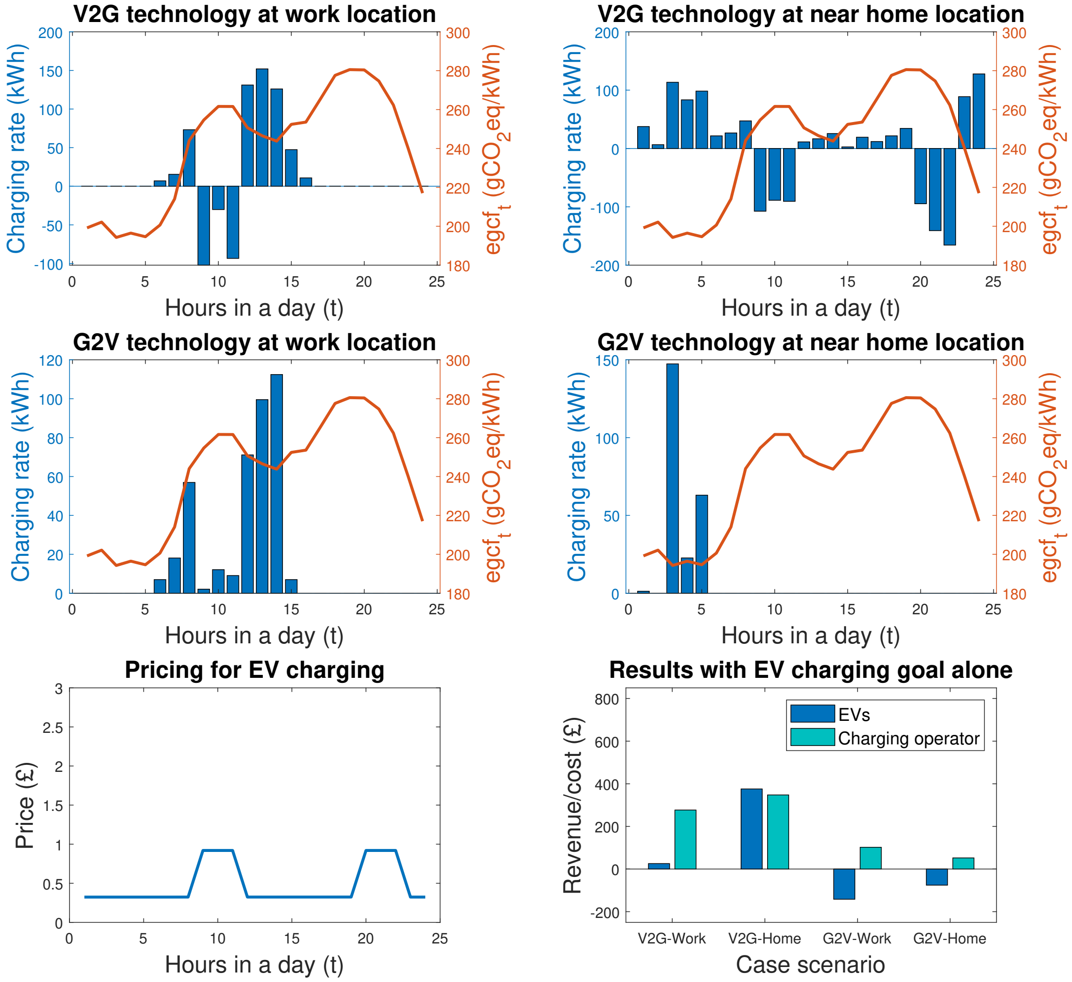


Figure 4.5: EV charging goal alone optimisation with EV charging schedules and revenues/costs with different charging technology and location.

station operator. The scenarios used for comparing EV charging schedules are based on technology; V2G (bidirectional) and G2V (unidirectional), and also based on stochastic EV driver behavior which includes arrivals and departures in locations of work and near home charging with varied trip requirements.

Figure 4.5 shows EV charging schedules obtained with EV drivers goal alone. The graph at the lower left corner shows the energy price that EVs will have to pay for energy and prices for selling energy to the charging station operator during carbon market trading timings. Slight changes of costs associated with carbon grid intensity levels in the form of a carbon tax is integrated in the price. Influenced by the slight price changes with carbon taxes imposed by a carbon regulator, EV charging schedules show most EVs are charged during lower electricity carbon grid factor in all charging case scenarios. This means that EVs behavior is adjusted depending on the energy mixed available every hour following low carbon intensity levels. However, in the G2V (unidirectional) case at work location, some charging happens during high intensity carbon grid factor as trip requirements should be satisfied. Another interesting pattern in the EV charging schedules is that with V2G charging technology, EV batteries can be discharged during allowed periods which are set up by the charging station operator from 9:00-11:00 hrs and from 20:00-22:00 hrs, note that these timings for regulation up and down were estimated according to the pricing strategy with price changes that are indicated by the number of EVs available for charging and the carbon intensity levels in the grid. Thus, V2G technology allows EVs to discharge energy during high carbon intensity levels, which is not the case of G2V charging where EV batteries cannot be discharged and need to be charged to meet driver requirements even if carbon levels are high. It can also be observed that work charging location offers less flexibility than charging near home, consequently EVs' availability for charging near home offers more potential for EV charging rate adjustments compared to charging at work.

Regarding revenues and costs, it can be observed on the graph at the lower right corner in Figure 4.5 that the scenario with more revenues for both EV drivers and the charging station operator is the one with V2G technology at near home location. EVs have the highest flexibility in this location, consequently EVs can take advantage of selling energy to the charging station operator while the charging station operator gets additional revenue from using EVs energy to sell to carbon markets. The second best option regarding revenue is also the V2G technology case but for the charging at work scenario, EVs and the charging station operator can both get revenues even with less EV battery flexibility available. In contrast, EV drivers are not able to receive any revenues with the two G2V cases due to the fact that they are only paying for the energy they need for charging at the lowest possible cost. The charging

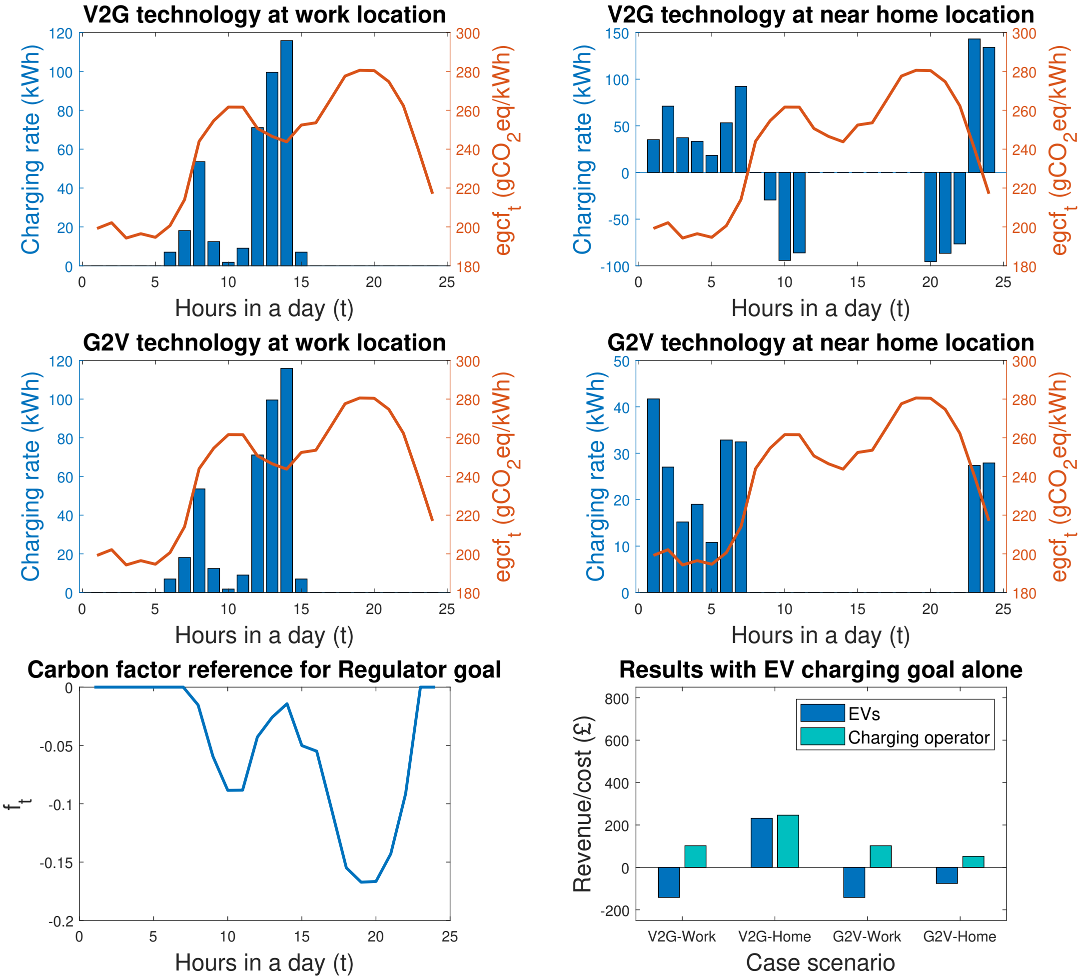


Figure 4.6: Regulator goal alone optimisation with EV charging schedules and revenues/costs with different charging technology and location.

station operator receives revenues from charging but does not earn money with an additional revenue stream as there isn't energy to bid/trade into carbon markets.

Results of EV charging optimisation with the regulator goal in Figure 4.6 show significant differences with EV charging schedules compared with the results obtained with EV drivers goal alone, specially in the V2G technology cases. The carbon regulator promotes charging based on a reference of carbon intensity levels whereas the EV driver goal promotes not only charging but also discharging if it is financially optimal. With the objective function of the carbon regulator, V2G charging is not necessarily encouraged, however V2G charging for home location offers the sufficient charging flexibility that makes EVs charge more energy than needed at low carbon intensity levels and then discharge energy at high intensity levels in order to meet trip requirements. Limited availability for charging of EVs in the case of work location with V2G technology makes it hard for EVs to discharge energy back to the grid. It can be observed that EV charging schedules for work and near home cases with V2G and G2V charging have less energy to bid to carbon markets compared to EV schedules with the EV goal due to the lack of incentives in the objective function to discharge energy back to the grid.

The lower right corner of Figure 4.6 shows the associated revenues and costs with the EV charging schedules. From the user perspective, EV drivers are able to get revenues only with the near home with V2G charging scenario thanks to the discharging energy they provide to the charging station operator. Interestingly, the V2G at work and G2V at work case scenarios are the EV charging schedules with more costs, this can be explained by the limited charging flexibility of EVs and the established high prices during carbon market timings. From the charging station operator point of view, the scenario with more revenues is the charging near home case with V2G technology. It can be concluded that, having the regulator goal as a single objective in the computation for EV charging schedules does not consider the benefits for discharging energy back to the grid in terms of potential extra revenues for both EV users and the charging station operator. Consequently, costs of EV users are less with the regulator optimisation than with the EV drivers optimisation. This could be attributed to bigger signals coming from the carbon regulator to charge at low cost energy related to low carbon intensity grid levels compared to the pricing incentives to users to allow discharging during carbon market specified timings.

To continue with the analysis of trade-offs coming from the EV charging schedules with optimisation using individual goals, Figure 4.7 shows EV charging schedules using the charging station operator goal alone. In this optimisation, the charging station operator already receives revenue form EV charging, therefore the goal of the charging station operator is to have an additional revenue stream with biding

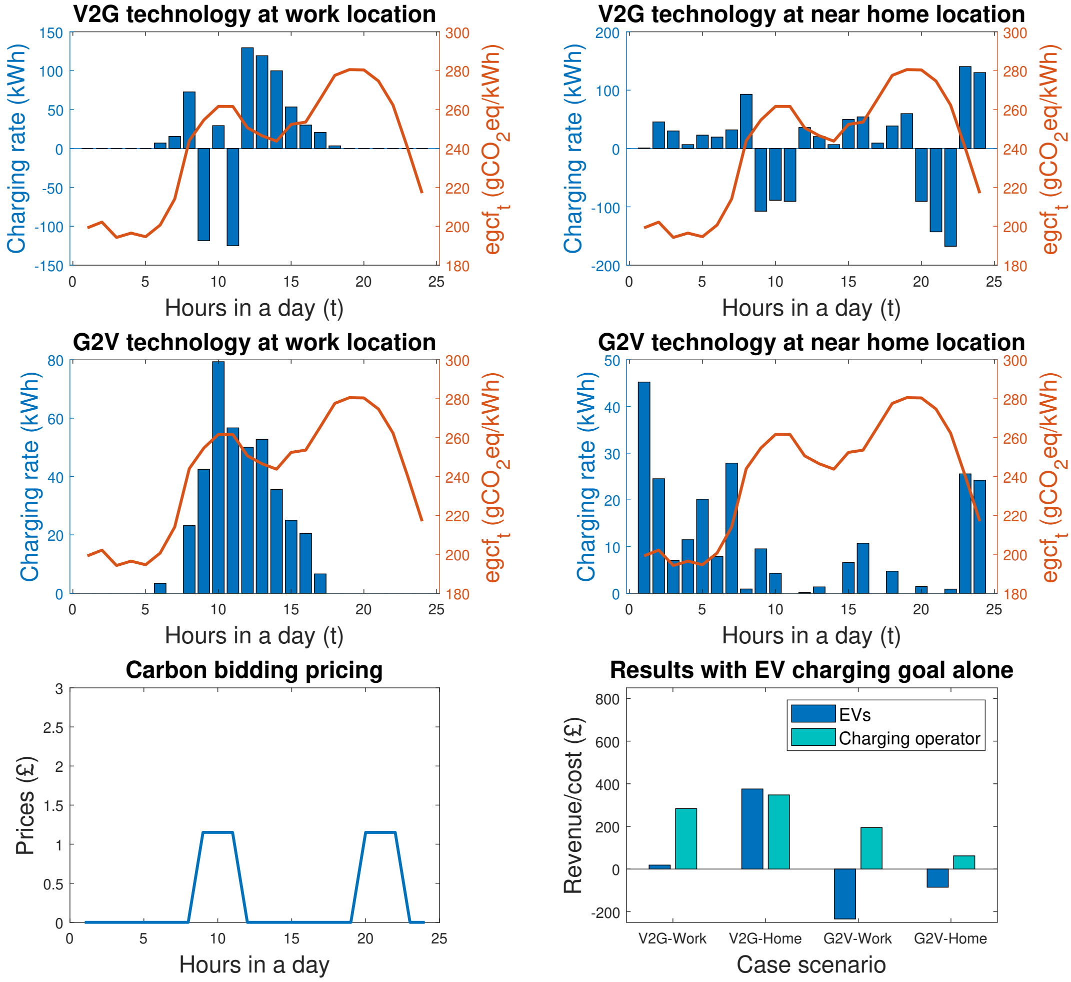


Figure 4.7: Charging Station goal alone optimisation with EV charging schedules and revenues/costs with different charging technology and location.

energy in carbon markets. Thus, the lower left graph at the corner shows the price offered for energy bidding quantities to carbon markets per kWh of energy coming from EVs. As it is expected, the scenarios with V2G technology offer more potentials of energy capacity, whereas G2V technology is limited to charging in one direction only and as a consequence, EV users are not able to support with energy trading in carbon markets. The scenario with V2G at near home location offers greater bidding capacity compared to V2G work location where EV flexibility is more limited. In this last case EVs need to charge energy at 9:00 hrs again to then be able to discharge energy in the next hour. Thus, greater bidding capacity and flexibility could come from using V2G technology with EV availability for near home charging.

The lower right graph at the corner of 4.7 shows the potential revenues obtained from EV charging schedules following the charging station operator goal alone. Note that the revenues for the charging station operator for all case scenarios are greater with the charging station operator goal alone compared to the results obtained with EV drivers goal. However, revenues for EV drivers are greater and costs are less with the results obtained following the EV users goal except for the V2G near home scenario. Differences between the charging schedules obtained with EV drivers goal and previous results that used the other two optimisation goals are more significant with V2G technology at work location. It can be observed in this case scenario that EVs need to charge with high energy prices during carbon market allowed timings to then be able to discharge with a higher bid for carbon trading in the last allowed hour slot. Thus, EV drivers can be disadvantaged if the charging station goal alone is used as they receive slightly less revenues relative to revenues with EVs goal case.

In conclusion, the best optimisation results in terms of revenues for the charging station operator with V2G technology are the ones computed with the charging station operator goal. Similarly, the best results with G2V technology cases are computed with the charging station operator goal. For EV users, the best optimisation results in terms of costs and revenues with V2G technology are the ones obtained with EVs goal, and also for the G2V technology cases, the best results are the ones computed with EVs goal. The carbon regulator goal did not prove to be the best option for either EV users or the charging station operator. However, it is important to compare impact on carbon emissions in EV charging schedules and fairness in relation to the weights assigned to each objective function for instance in a multi-objective formulation. These two aspects of comparison are explored in the following two subsections.

### 4.4.2 Comparing Fairness

The previous section showed that expected revenues for EV drivers and the charging station operator differ when the individual objectives are used for modelling EV charging schedules. The aim of the analysis in this section is to study the results obtained with the multi-objective genetic algorithm and analyze selection of optimal solutions that can lead to a fairest solution and to a greenest solution. The three goals which include interests of EV drivers, a carbon regulator and a charging station operator are modelled as a multi-objective optimisation with V2G charging technology only. The reason for this is that the charging station operator does not have a significant influence over G2V technology with the current model proposed and thus is more reasonable to model fairness between these 3 goals with V2G. Therefore, contrasting multi-objective goals are presented for V2G charging near home and for charging at work which have variations in stochastic EV driver availability for charging (flexibility) and trip requirements.

Figures 4.8 and 4.9 show the values of the multi-objective genetic algorithm search for optimal solutions in several generations. The graphs at the left show the values of the three goals separately and the graphs at the right show the value of the weights explored for each normalised objective function. To avoid confusion when estimating the values in the objective functions, the values of the objective functions presented in the graphs for the EV drivers and the charging station operator are positive, and the values of the regulator are non dimensional and negative. For practical purposes total number of generation runs was 5 with 48 individuals for the two cases, however non-dominated solutions in a generation in pareto frontier 1 (best evaluation of non-dominance and crowding distance), could was reached since generation 2, further changes of non-dominance are highly unlikely.

Figure 4.8 presents the results obtained for the multi-objective genetic algorithm at work charging location with V2G technology. The design variables which were the weights for each objective function $\alpha_j$, $\beta_j$ and $\gamma_j$ observed in the graph at the

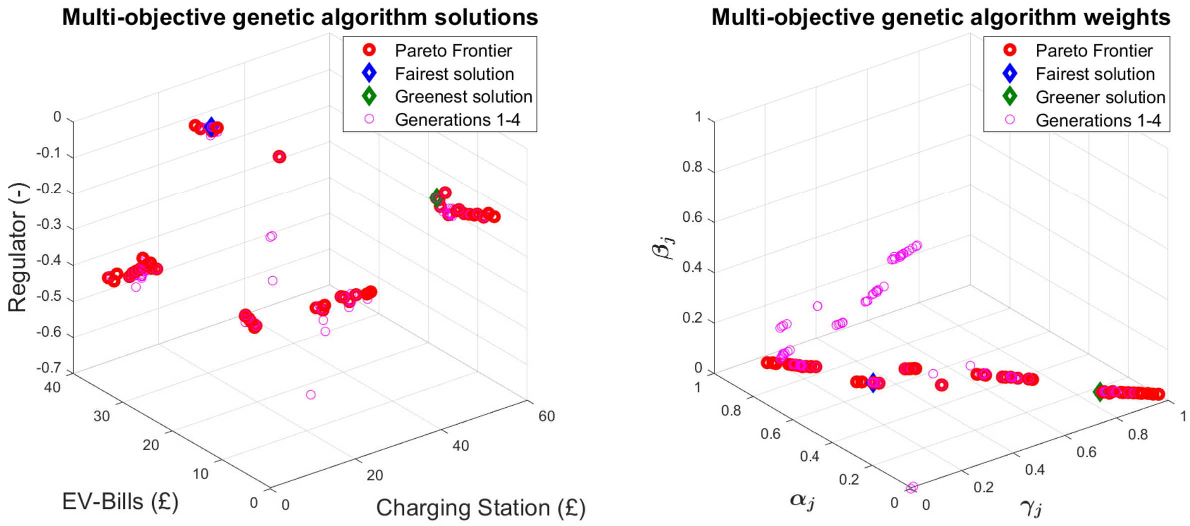


Figure 4.8: Comparison of objective function values and weights obtained with multi-objective genetic algorithm for charging at work.

right, show that convergence of the design variables is more predominant towards interaction goals of EV drivers and the charging station operator. Regarding the graph with objective function values at the left, it can be observed that the range between the maximum and minimun objective function in the pareto frontier is greater with the charging station operator, then with EV drivers and then the regulator. This indicates the charging station operator has the greatest cost of opportunity in this model, however it is important to consider that total revenues for the charging station operator are not integrated as current objective function values in the graph only consider the revenues obtained from carbon market trading participation. Therefore, there could a greater cost of opportunity from an EV user perspective. It is also important to mention that the carbon regulator is modelled as a non dimensional objective function to encourage charging during a reference to low intensity levels, therefore it does not receive any revenues.

In terms of the selection of the fair solution from the pareto frontier in the left graph in Figure 4.8, the fairest solution has weights of approximately 0.65 assigned for EV drivers, 0 weight assigned to the carbon regulator (regulator would not have any value in the objective function), and 0.35 weight for the charging station operator. This

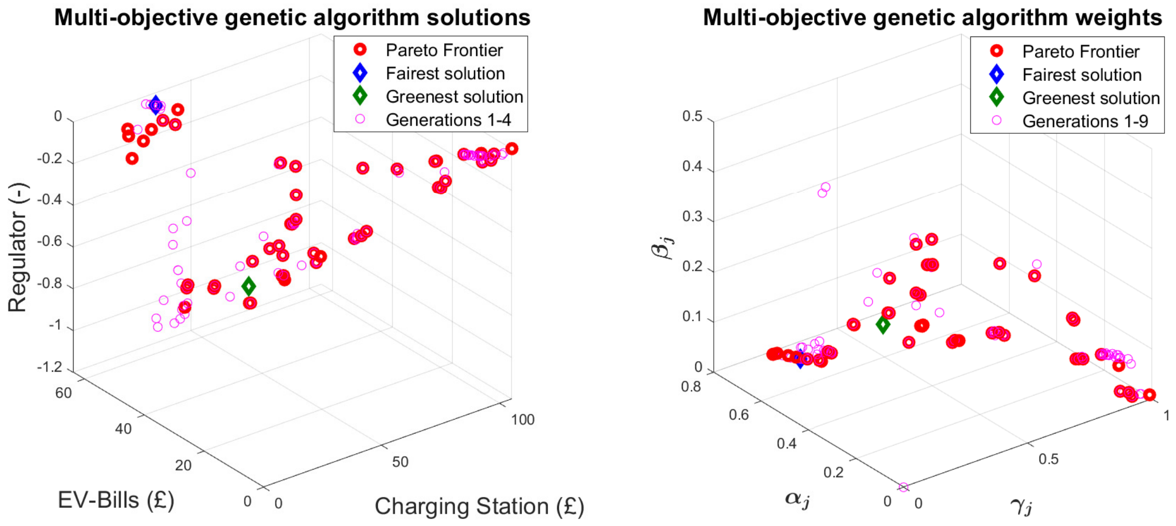


Figure 4.9: Comparison of objective function values and weights obtained with multi-objective genetic algorithm for charging near home.

result suggests that a fair strategy for estimating EV charging schedules may come from giving EV users priority when estimating charging schedules as EV drivers are affected by the carbon tax variations imposed in energy costs and have the interest to provide energy back to the grid. This could help both the carbon regulator and the charging station operation interests to reduce carbon emissions and to support the grid in carbon market participation respectively. With regard to the green solution, the selected optimal solution comes from weight of approximately 0.84 assigned to the charging station operator, followed by a 0.13 weight assigned to EV users and 0.03 weight assigned to the carbon regulator. The weight values of this green solution may indicate that the charging station operator and EV users together have more impact on $C0_2$eq emissions than the carbon regulator in this case scenario. An explanation for this result could be that EV driver availability may be limited, and therefore they may want to charge even at high intensity levels to meet driver requirements, which is not convenient to the carbon regulator formulation.

Figure 4.9 presents the objective function values and weights explored for the multi-objective optimisation case of V2G technology for charging near home. Compared with the convergence of the design variables of the pareto frontier in the work charging case discussed in previous paragraph, the weights in the right graph of Figure 4.9 converge also towards goals of EV drivers and the charging station operator, but some solutions also include weights assigned to the carbon regulator. Similar to the work location charging case, the objective with greatest opportunity cost, that is the objective with highest range between the minimum and maximum possible value for the optimal solution, is the charging station operator goal followed by EV drivers and the regulator. However, it is important to note that EVs could be more disadvantaged because they do not set pricing for energy and customer satisfaction is not considered in price set up established by the charging station operator.

The results of weights used for selection criteria for the fairest solution were of approximately 0.73 for EV drivers, 0 for the regulator and 0.27 for the charging station operator. It is possible that with greater flexibility of EV drivers, the charging station operator could have less influence over a fair solution compared to the fairest solutions of the work charging case where the charging station operator had a bigger weight. The greenest solution has a approximate weight of 0.50 assigned to the EV drivers, a weight of 0.11 assigned to the carbon regulator and a weight of 0.39 assigned to the charging station operator. This is a contrasting result compared with the work charging case where the charging station operator had the highest weight in the multi-objective solution. In general, EV drivers had the highest weight assigned for both fair and green solutions at work and near home charging locations except for the green solution at work where the charging station operator had the highest weight.

### 4.4.3 Comparing EV Potential to Reduce $CO_2$eq Emissions

The intention of the formulation proposed in this Chapter with a multi-objective optimisation approach is to test how different objectives may influence EV charging schedules to reduce $CO_2$eq emissions as much as possible, either by following pricing signals with added carbon taxes according to carbon intensity levels, by trading

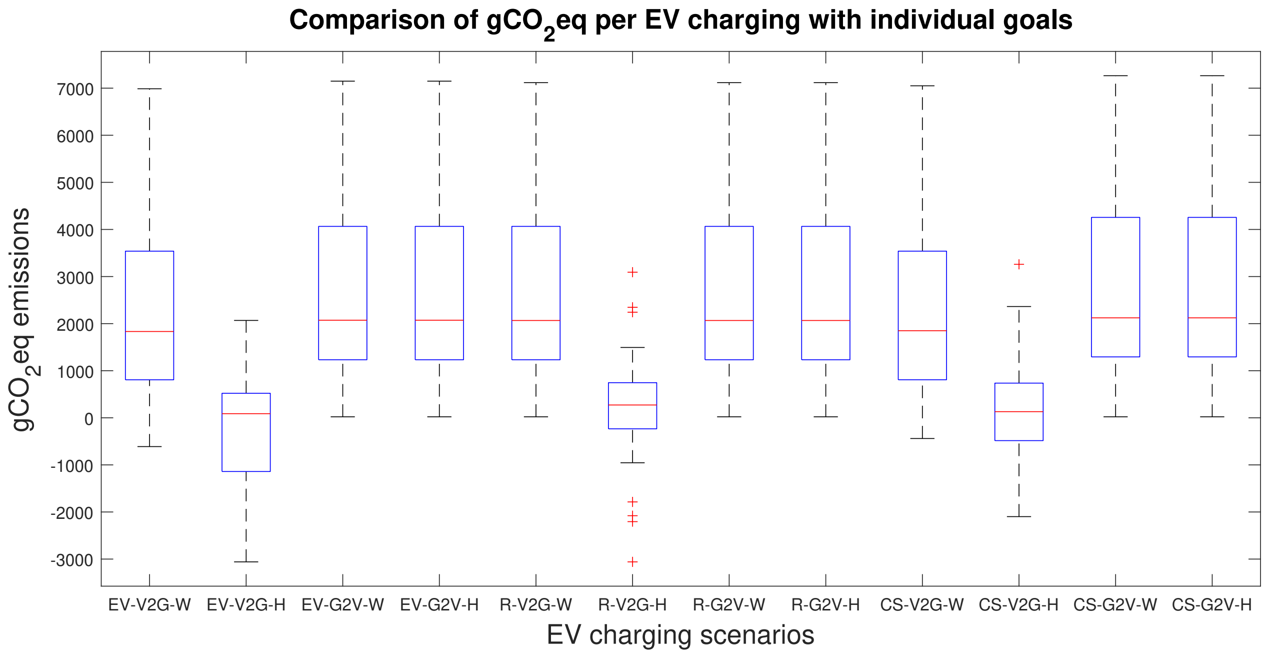


Figure 4.10: Comparison of EV charging schedules with independent objectives with nomenclature of: individual goal (EV-electric vehicles/ R-regulator/ CS-charging station operator) - EV Technology (V2G-bidirectional/ G2V-unidirectional) - charging location (W-work/ H-near home).

energy with carbon markets or just by charging energy when it is more convenient based on the carbon intensity of energy generation mix at the grid level. Figure 4.10 shows a box plot comparison of descriptive statistics related to the carbon emissions from EV charging schedules depending on the optimisation with individual goals, the technology used and the charging location scenario. Lowest $CO_2$eq emissions are possible with V2G technology at near home location starting with EVs goal, followed by the charging station operator goal, and in third place is the regulator goal. From these results we can see that the biggest opportunity to minimise $CO_2$eq emissions is in the near home scenario where EVs have more shiftable energy load that follow signals related to carbon grid intensity levels. Another key insight about these results is that V2G technology provides greater environmental benefits as EV batteries can discharge energy back to the grid at high intensity levels and charge at low intensity levels. Note that, the mean electric carbon factor for the lowest scenario of $CO_2$eq emissions is negative, this means that there is potential support

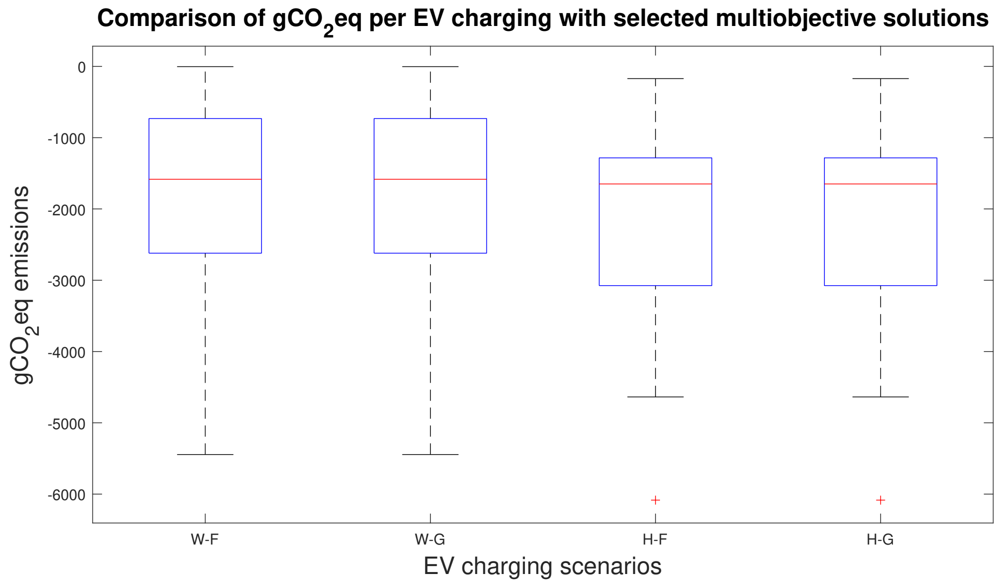


Figure 4.11: Comparison of EV charging schedules with multi-objective optimisation solutions for different scenarios with nomenclature of: charging location (W-work/H-near home) - solution(F-fairest/G-green).

with carbon offset mechanisms.

The transition to a carbon zero economy could come from real restrictions imposed to comply with carbon regulations. Thus, the conflicting objectives in the multi-objective formulation will need to be resolved in a real case scenario to find a balance between weights assigned to each objective. The potential of the fairest and green solutions, obtained with multi-objective genetic algorithm, to minimise $CO_2$eq emissions is compared in Figure 4.11. This box plot shows that the solution with lowest environmental impact is both the greenest solution for the charging case at near home location and the fairest solution also for the charging case near home. Interestingly, solutions of the pareto frontier have similar $CO_2$eq which means that actually the minimisation of these emissions could be highly related to trip and charging flexibility of EV users. Similar to the comparison of the individual goals in Figure 4.10, the solutions with more potential to minimise $CO_2$eq emissions are the ones associated with near home charging case scenarios with V2G technology where EVs can be charged at night during low intensity carbon levels and be discharged during the day if possible, to participate in carbon markets when high carbon intensity levels occur.

## 4.5 Chapter Remarks

### 4.5.1 Discussion

In this Chapter, a multi-objective optimisation strategy for EV charging is proposed to minimise carbon emissions. The optimisation included three conflicting objectives represented by EV drivers, a carbon regulator and a charging station operator. The three objectives showed differences in terms of the revenues/costs of EV drivers and the charging station operator, and in terms of $CO_2$eq emissions attributed to EV charging schedules. Higher differences of revenue trade-offs were found with conflicting interests between both the charging station operator and EV drivers, against the results obtained with the carbon regulator. Results, also showed that the biggest potential to reduce $CO_2$eq emissions from EV charging could come with V2G technology and flexibility of EV users from a near home case scenario. Nevertheless, the model proposed in this Chapter has limitations, for instance it is assumed that carbon markets are available at timings, energy price and quantity bidding specified by the charging station operator, thus the carbon market operator is able to make an energy contract with the charging station operator from a day ahead planned schedule.

Improvements to the model proposed can come from the formulation of the multi-objective optimisation model. For example, the carbon regulator encourages charging at a reference point of low intensity levels but doesn't consider capability of V2G, which could also help minimise carbon emissions for the whole charging schedule and support with balancing mechanisms that could be matched with intermittent nature of renewable generation. In the multi-objective optimisation proposed in this Chapter, theoretical interests were modelled, and thus practical enablers need to be considered to support low carbon and fair strategies. Some barriers identified for the development of low carbon EV charging are related to regulatory framework to introduce carbon taxes, support to carbon trading schemes at the regional level where EV battery aggregation can be beneficial to the distribution system or even at the transmission level if the capacity bid is sufficiently big. More emerging markets are also needed to support the inclusion of flexibility potential of EVs. In addition, customer engagement is necessary to use EV batteries as flexibility assets, thus it is important to consider customer satisfaction and willingness to act as business partners in potential value proposition models.

### 4.5.2 Conclusion

This Chapter presented a modelling approach for EV scheduling to reduce $CO_2$eq emissions used when charging EVs. A multi-objective optimisation was formulated where potential conflicting interests came from the perspective of EV drivers, a carbon regulator and a charging station operator. The potential revenues/costs for EV drivers and the charging station operator were compared when using the optimisation with individual objectives, the best options for both EV users and the charging station operator were the solutions found with their respective goals computed separately when using V2G technology. A multi-objective genetic algorithm was proposed to find a fair and a green solution considering the trade-offs of each goal. There was a tendency towards higher weight factor assigned to the EV drivers goal in all solutions except the green solution found for the work case scenario where more weight was assigned to the charging station operator. Thus, a priority on the goal proposed for EV drivers has potential for finding fair and green solutions specially where V2G technology is present and where EVs have more charging flexibility.

Opportunities of research in future directions could include further additions where EVs can be integrated to support the transition to decarbonisation with power systems modelling. For instance, at the micro-grid islanded level where EVs can support with storage capacity at residential locations or at work/supermarket locations where

EVs can be integrated with buildings. Degradation restrictions of batteries and more uncertainties of EV driver behaviour such as unexpected departures, can also be further studied to improve the accuracy of EVs capacity to be modelled as flexible loads. Due to the model proposed has high computational time, it may have limited application to cases where planning in advance for bidding into market auctions is possible, thus a faster real time control for EV charging schemes could also be integrated to consider real scenarios where latency response and grid restrictions are important. Finally, another research direction for EV charging could include peer trading mechanisms with carbon factor considerations.

# Chapter 5

# Sensitivity Analysis of EV Charging Parameters

## 5.1 Introduction

The two previous chapters have proposed pricing and bidding mechanisms for participation of EVs in different markets. Firstly, in balancing services and secondly in carbon markets. The aim of this chapter is to provide key variables that can be improved from the models proposed in Chapter 3 and 4. In specific, this Chapter tackles ***Objective 5*** described in the Introduction section of this thesis. ***Objective 5*** is to analyze what parameters can improve the performance of a charging station operator stakeholder. The contribution in this Chapter related to this objective is the strategic assessment, made with sensitivity analysis using one at a time method, to evaluate selected parameter inputs measured by performance indicators of $CO_2$eq emissions, bidding capacity to be used in market auctions, revenues and costs for both EV users and the charging operator.

EV charging optimisation modelling has been extensively studied in the previous two Chapters, it is important to determine improvement opportunities (for both researchers and industry stakeholders) and limitations of the models proposed. For practicality, the parameters to study in the sensitivity analysis of this chapter are divided into parameters that can by controlled by the charging station operator and parameters that depend on EV driver behavior or technology. Parameters that could be controlled by charging station operator include initial state of charge of an EV, trip requirements (when the charging station may sacrifice customer satisfaction for instance when there are grid restrictions) and the size of the charging station. Parameters that are independent of the charging station are EV availability, EV battery size and charging rating of EVs. Indicators for the changes in the parameters to study consider revenues of the charging station operator, bills of EV users, $CO_2$eq emissions per the charging schedule and bidding capacity to bid when discharging energy from EV users. It is important to note that charging with unidirectional technology in the last indicator is not considered as discharging of energy can work for both carbon and balancing markets.

## 5.2 Problem Formulation

The previous two Chapters have provided significant contributions to the areas of demand side management and multi-objective formulations to reduce carbon emissions. This Chapter focuses on investigating sensitivity of selected parameters used in the models from Chapter 3 and Chapter 4. The aim of the sensitivity analysis is to investigate which parameters can provide the best response considering revenues for the charging station operator, bills savings from EV users, reduction of $CO_2$ emissions and bidding capacity. The sensitivity analysis previously described provides potential improvements in the operation of a charging station that can be key for further work in the topic of overall integration of EVs with the grid. In addition, the sensitivity analysis provides insights for asset modeling potentials for future work using the models proposed in previous Chapters.

Research works in sensitivity analysis of electric vehicles have provided insights to future asset modeling capabilities. For instance, Stiasny *et al.* [157] investigated impact of EVs in the low distribution grid and found highest sensitivities are observed with increasing number of EVs, increase of pole charging rating and movement of EV patterns. Zhou *et al.* [158] proposed a sensitivity analysis for techno-economic assessment of varied microgrid settings with EVs, results showed highest sensitivity impact on revenue is observed when changing battery storage system cost. Zhu *et al.* [159] assessed vehicle life-time costs with a sensitivity analysis for supercapacitor energy storage systems, results concluded that highest costs are observed in battery degradation, more specifically the sensitivity results indicated highest impact from battery degradation are observed in vehicle driving range. The previously mentioned authors have used in their sensitivity analysis one of the two methods: one factor at a time, where one input changes while the others remain constant, and global sensitivity analysis, where more than one input can vary simultaneously [160]. For practicality, one factor at a time method is used in this Chapter for the simplicity of identification of isolated changes that can improve performance of the model.

The EV charging model to optimise from EV users perspective in Chapter 3 demonstrated how users can respond to pricing schemes created by the charting station operator. Then in Chapter 4, EV charging schedules were created in a multi-objective optimisation where pricing signals also consider carbon taxes imposed by a carbon regulator. Thus, the pricing scheme in this Chapter considers the pricing strategy extension from Chapter 4 (extension of Chapter 3) to take into account additional costs associated to EV charging. Thus, pricing strategies are formulated using equations 3.2.1 through 3.2.20, with additional carbon tax costs stated 4.2.8. Timings for influencing EVs to discharge energy back to the grid and for setting energy bids are estimated with equations of high carbon grid intensity as stated in 4.2.10 and high capacity of the charging station as in 3.2.12.

Regarding the EV charging optimisation model to use in this Chapter, one goal from the multi-objective optimisation is selected in order to examine EV charging schedule sensitivities when adjusting different parameters. For this purpose, the goal selected is EV users' as was the goal with overall highest weight with both

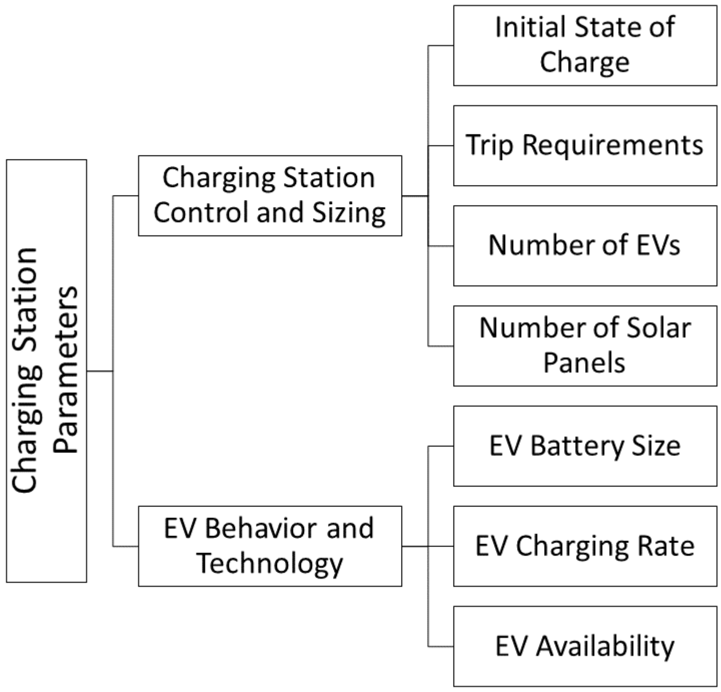


Figure 5.1: Selected parameters to model in the sensitivity analysis.

the fairest and greenest solution based on the results obtained from the genetic algorithm used in Chapter 4. Thus, EV charging schedules are analyzed using the model formulated with equations 3.2.21 through 3.2.27. Restrictions from the EV charging formulation from a carbon allowance per EV impose by a carbon regulator in equation 4.2.6 is not considered in this Chapter this restriction may over restrict the formulation and cause potential infeasibilities in the sensitivity analysis. All parameters to be analyzed in this Chapter with the pricing and EV charging just described, are summarised in Figure 5.1.

## 5.3 Evaluation of EV Charging Parameters

Simulation parameters to be used for the sensitivity analysis can vary depending on which parameter is being studied. General parameters of all sensitivity cases can be summarized in Table 5.1, however there are few exceptions to the calculations as some parameters must remain fixed when changing others. Sensitivity analysis for the initial state of charge of an EV was estimated when making variations of the

Table 5.1: Simulation parameters

| Parameter | Value |
|---|---|
| Total number of EVs | 35 EVs |
| Carbon tax ($ctax_t$) | 18 £/ton$CO_2$eq emissions |
| Solar panel rating | 4 kW [139] |
| Time periods in a day | 24, for every hour |
| EV arrivals (home) | Empirical cdf [156] |
| EV departures (home) | Empirical cdf [156] |
| Initial state of charge (home) | Empirical cdf [156] |
| Trip requirements (home) | Empirical cdf [156] |
| EV arrivals (work) | $ar \sim \mathcal{N}(\mu = 8, \sigma^2 = 1)$ [138] |
| EV sojourn time (work) | $ts \sim Logistic(\mu = 0.27, s = 0.06), mn = 5, mx = 18.52$ [138] |
| Initial state of charge (work) | Empirical cdf [140] |
| Trip requirements (work) | Empirical cdf [140] |
| Charging station rating | 3.7 kW [141] |
| Mitsubishi Outlander charging ratings/battery size | 3.7 and 22 kW/ 12kWh[142] |
| Nissan Leaf charging rating/battery size | 6.6 and 50 kW/40 kWh[143] |
| BMW 330e charging ratings/battery size | 3.7 kW/12 kWh[144] |
| Energy cost | 10 p/kWh [146] |
| Utility from carbon markets | 10% |

percentage of state of charge from nearly 0% to 100% of the battery size. As the EV charging formulation uses stochastic trip requirements as a restriction, the value of this parameter had to be adjusted to meet charging rate and battery size restrictions. Sensitivity analysis of trip requirements used from original trips from stochastic requirements in Table 5.1 was modelled with percentage increases from 0% to 100%. However, restrictions of battery size and charging rate were also checked. Increase in the infrastructure of the charging station in terms of solar panels available was increased from 1 to 200.

In terms of parameters external to the control of the charging station operator, increase of battery size of EVs was simulated from 12 kWh to 300 kWh. Similarly, sensitivity analysis was simulated with charging rate of EVs increasing from 3.7 kW to 193.7 kW. For these two sensitivity analysis, all other parameters in Table 5.1 were used except for the ones just described. Finally, as EV arrivals and departures are simulated as availability of EVs at the charging station with a binary matrix, EVs availability hours for charging was decreased from arrivals and departures at the same time starting from two hour reductions to maximum 20 hours, where zero availability was set if there were no longer hours to reduce from EVs availability. For this sensitivity analysis, trip requirements were checked and updated to reflect potential restrictions of battery size and charging rate as less availability for charging means the EV charging optimisation can become infeasible if trip requirements are not satisfied.

### 5.3.1 Charging Station Control and Sizing Parameters

This Subsection shows the sensitivity analysis of the results obtained when charging parameters of initial state of charge of EVs, trip requirements, number of solar panels used for energy generation at the charging station and number of EVs at the charging station. The first two parameters are analysed as it is assumed that if the charging station operator is the only provider of EV users, for preference, convenience or price, then it could be possible to control for instance the final state of charge of a vehicle in a specific location and/or limit trip charging requirements which are normally specified by EV users. The last two parameters are regarding the size of a charging station, these two are analyzed to project what is the impact on the number of charging poles available for charging and the size of a potential renewable charging station that uses solar panels to charge EVs as much as possible.

Figure 5.2 shows the sensitivity analysis performed when the initial state of battery for a mix of EVs with stochastic charging rating, battery size and trip requirements as the ones used in Chapter 4 for home and residential locations. Initial state of charge was obtained by increasing percentage of the total battery size of each EV. Revenues for the charging station operator decrease in the two G2V cases as the initial state of charge reaches 100%, however revenues increase with the V2G work case and the V2G home case remains relatively stable with slight reduction in utilities. The reason for this could be that V2G technology allows discharging regardless of the

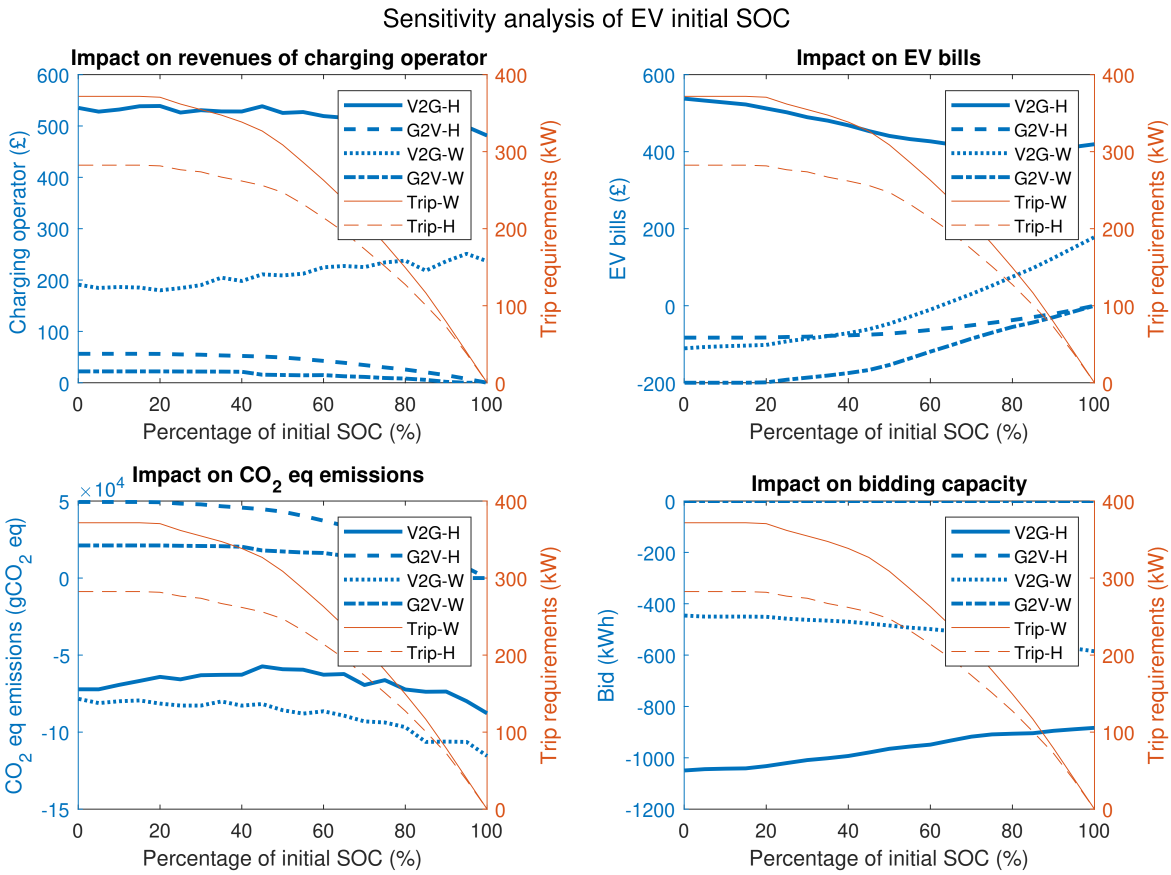


Figure 5.2: Sensitivity analysis of initial SOC of EVs with case scenarios with nomenclature of: EV Technology (V2G-bidirectional/ G2V-unidirectional) - charging location (W-work/ H-near home) and Trip Requirements (Trip) - charging location (W-work/ H-near home).

initial state of charge as long as the final state of charge meets driving requirements.

Moving on with the results in Figure 5.2, EV bills are positive (meaning EV users get utilities) no matter the initial state of charge of an EV with the V2G home case. Whereas, EVs have costs with the three other cases but EVs eventually start having less costs as the initial state of charge increases, specially in the V2G work case where EVs even get utilities between the 40% and 60% of initial state of charge. This means that as EVs get higher battery charge, they get more utilities as they are providing energy back to the grid when having vehicle to grid technology. As unidirectional technology is limited to just charging, with higher battery charge EVs can only reduce charging costs. In terms of carbon emissions from EV charging,

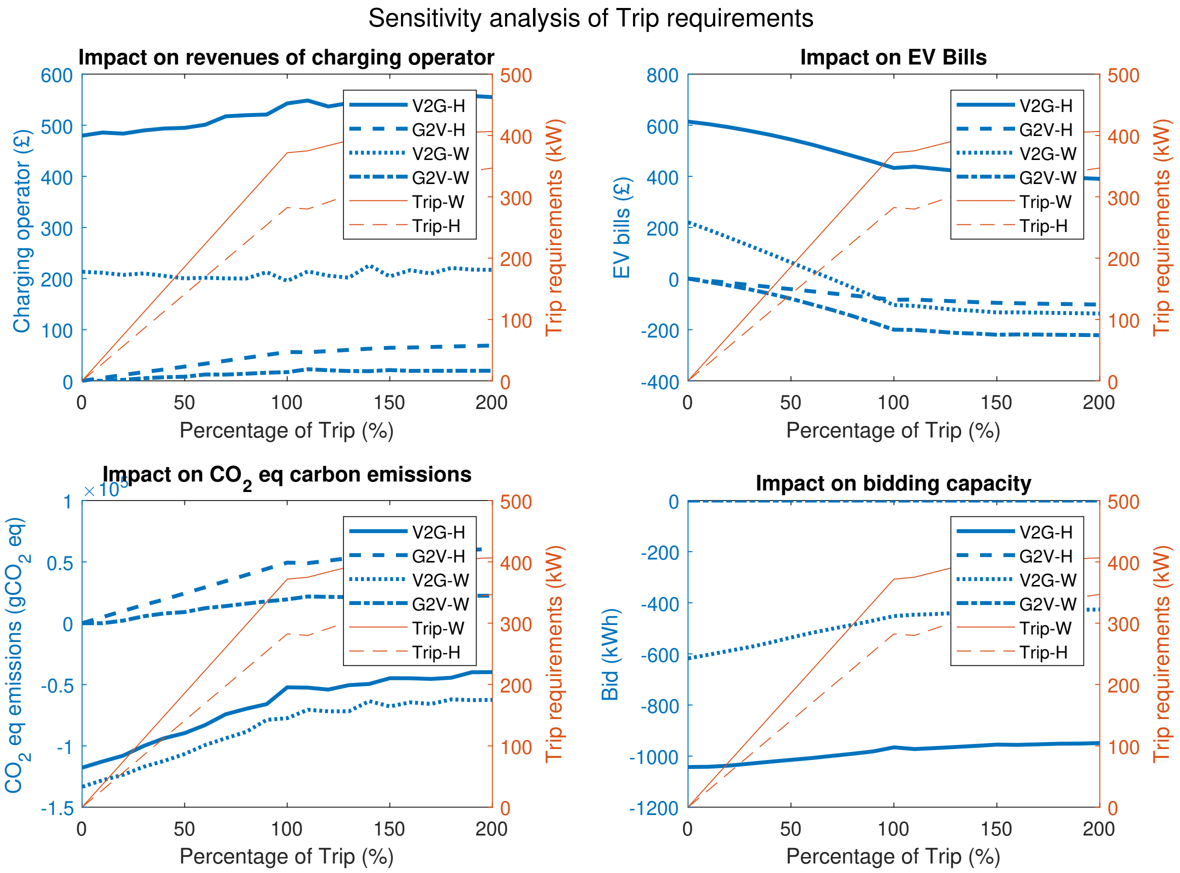


Figure 5.3: Sensitivity analysis of Trip Requirements of EVs with case scenarios with nomenclature of: EV Technology (V2G-bidirectional/ G2V-unidirectional) - charging location (W-work/ H-near home) and Trip Requirements (Trip) - charging location (W-work/ H-near home).

most cases have a decrease in carbon emissions as the initial state of charge increases except for the V2G home case where maximum $CO_2$eq emissions are located between the 40% and 60% percentage of the initial state of charge of the battery. Finally, bidding capacity increases as the initial state of charge increases in the V2G work case, whereas bidding capacity decreases with increase in initial state of charge in the V2G home case. Thus, bidding capacity can be maximised as EVs arrive at home with low battery charge and and as EVs arrive with high battery charge at work locations. The control of state of charge could potentially be managed by a single charging provider and an accurate estimate of trips and charging scheduling.

Figure 5.3 shows the results of the sensitivity analysis of variations of trip requirements. Revenues of the two G2V cases and V2G home case increase as trip requirements increase, however there is no clear trend in the V2G work case. In terms of EV charging costs for EV users, they start increasing as trip requirements increase, however as trip requirements reach 100%, the slope of EV bills decrease at a lower rating than before reaching the 100% trip requirements. This could mean they are restricted either by the charging rating or battery size of EVs. Similarly, the impact on increase of $CO_2$eq emissions is more prominent before trip requirements reach 100%. Bidding capacity decreases for both the V2G home and work cases, higher capacity is observed in the home case as EVs have more flexibility. If we compare the biggest bid in the V2G home cases of the sensitivity analysis of trip and initial state of charge control, initial state of charge offers slightly more bidding capacity, however difficulties of control and customer satisfaction should be considered as well.

Figure 5.4 shows the sensitivity analysis when increasing the capacity of the charging station for instance in a public parking hub or in a specific residential area where EVs can be aggregated as flexible loads. Revenues for the charging station operator increase in all case scenarios specially in the two V2G cases. Utilities for EV increase in the two V2G cases with a higher increase proportion in the home case scenario. In contrast, EV bills are negative in both the G2V cases as EV number increases and selling energy back to the grid is not possible with unidirectional technology. Moving on to the impact on $CO_2$eq emissions, as the number of EVs to aggregate increases, $CO_2$eq emissions decrease only in the case of the V2G home case scenario. Meanwhile, all other cases have an increase in $CO_2$eq emissions as the number of EVs increases. Regarding bidding capacity, the most significant change as the number of EV increases is in the V2G home scenario where capacity reaches about 1.87 MW with 96 EVs. Capacity with the V2G work case scenario also increases up to about 1.14 MW. When aggregating the total bidding capacity of both charging technologies, both meet minimum bid requirements of National Grid (transmission system operator in the UK) however it is important to consider that the same bidding capacity must be sustained for the periods specified by the aggregator.

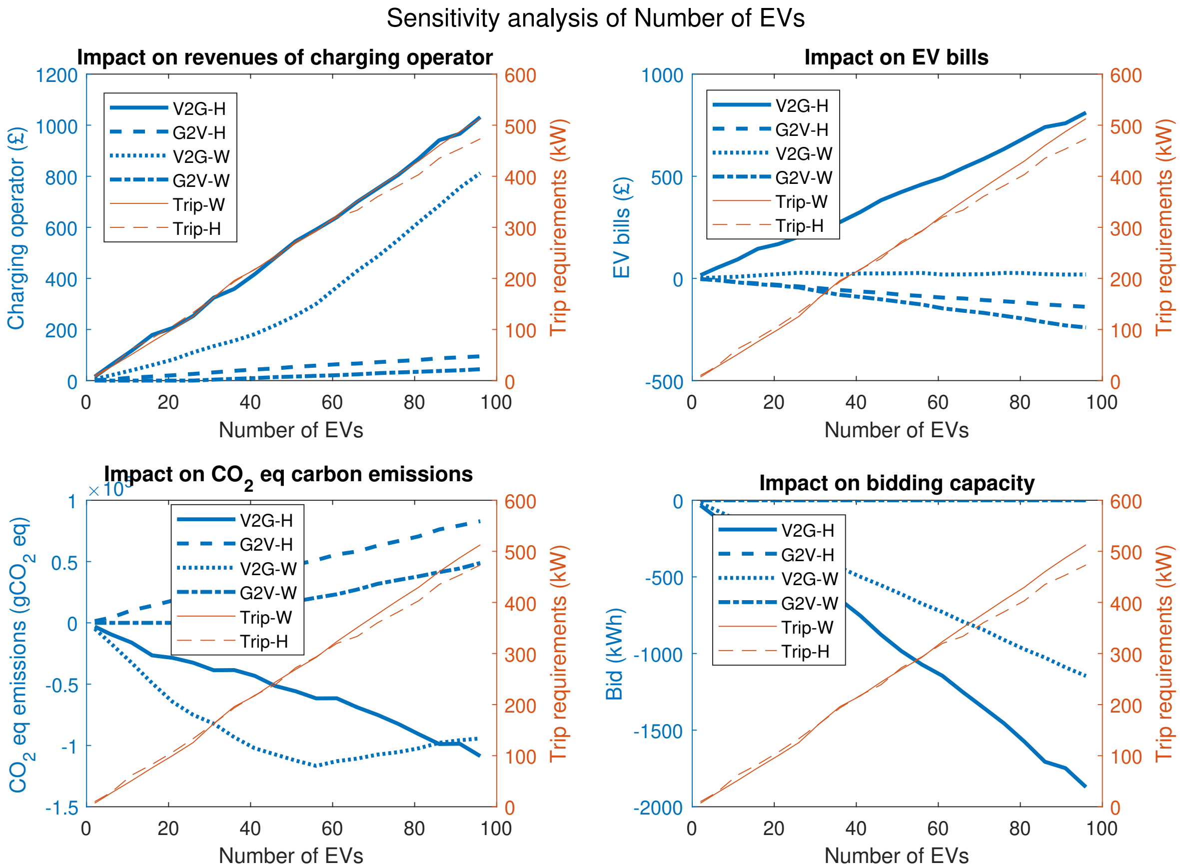


Figure 5.4: Sensitivity analysis of Number of EVs with case scenarios with nomenclature of: EV Technology (V2G-bidirectional/ G2V-unidirectional) - charging location (W-work/ H-near home) and Trip Requirements (Trip) - charging location (W-work/ H-near home).

Sensitivity analysis as the number of solar panels increases is presented in 5.5. For this analysis it was not required to change trip requirements for work and home location. It can be observed in the top left graph that an increase of solar panels has the biggest impact in the case of V2G at work location followed by the V2H work case. As solar power overlaps with EV driver behavior at work location, the work cases show biggest impact on revenues of the charging station operator than the results obtained with home location. However, as pricing per unit remains the same as the pricing strategy depends mainly on user response to prices, that is price does not decrease with increasing number of solar panels, then EV bills remain constant. $CO_2$eq emissions are reduced the most with the V2G work case scenario as a result

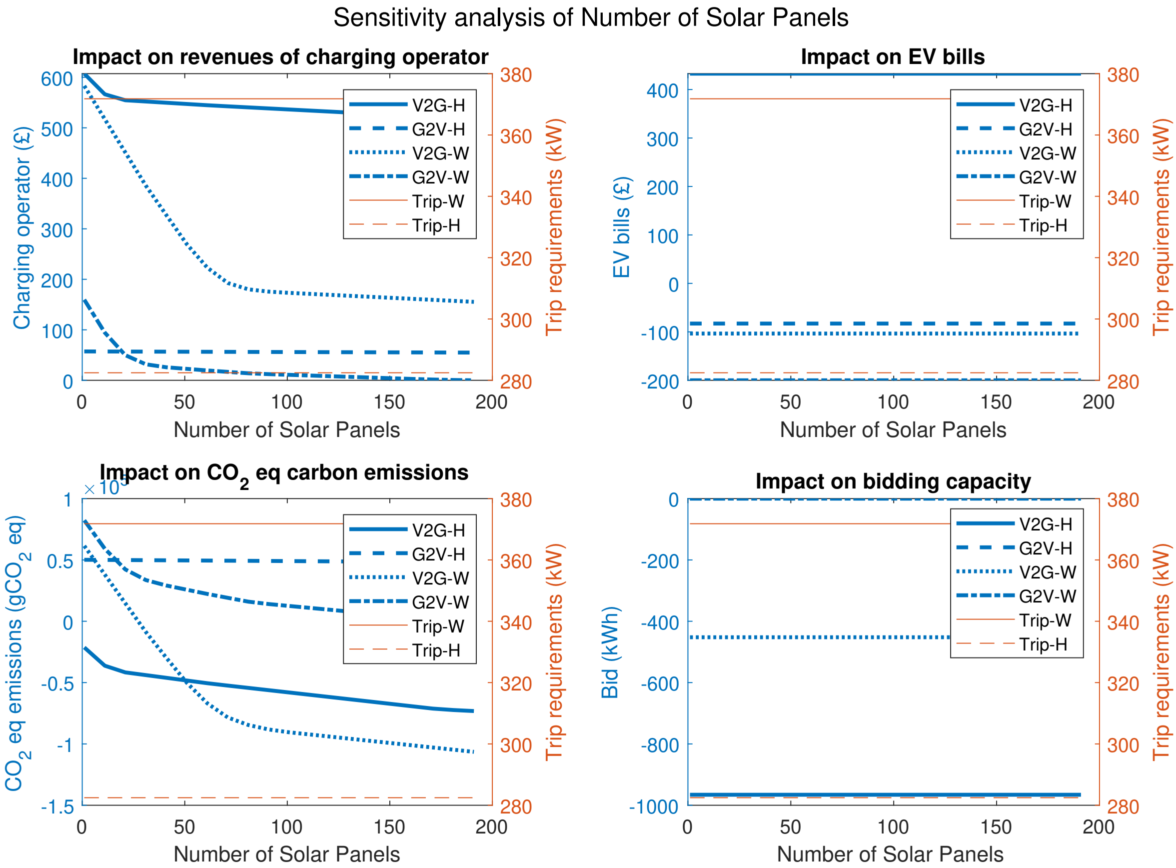


Figure 5.5: Sensitivity analysis of Number of Solar Panels with case scenarios with nomenclature of: EV Technology (V2G-bidirectional/ G2V-unidirectional) - charging location (W-work/ H-near home) and Trip Requirements (Trip) - charging location (W-work/ H-near home).

of solar power generation overlap with EV charging availability for charging behavior at work location. The V2G near home case offers the second best option in terms of minimisation of $CO_2$eq emissions followed by the G2V work and finally the G2V near home case. Bidding capacity remains constant as flexibility is aquired only form electric vehicle batteries.

### 5.3.2 EV User Parameters

To continue with the sensitivity analysis presented in this Chapter, this Subsection contains the parameters that are depending on EV driver behavior and technology; EV charging rate restrictions, battery size and EV availability (arrival to departure at the charging station). The results obtained assume the charging station rating restrictions are not constrained and therefore the charging limitations are set by EV owners. Similarly, battery sizing does not depend on infrastructure of the charging station, and therefore it is included as an external factor of the charging operator. To better represent the impacts in battery and charging rate increases, it is assumed that all EVs have the same technology specifications. EV availability is considered in this subsection as EV behavior does not necessarily depend on the charging station sizing or charging control. However, prediction to arrival and departures is possible with forecasting information which can be somewhat in control of the charging station operator. Analysis of the results obtained when increasing the parameters described are presented in the following paragraphs.

Figure 5.6 shows the results when increasing EV battery size. As requirements for charging and charging rate restrictions remain constant, the impact on revenues of the charging station operator only increase in the V2G cases where the battery size of EVs could be charged and discharged to minimise EV bills. In a similar way, EV bills (utilities) increase with charging rate only for the two cases of V2G, but this is limited as well by trip and charging rate restrictions of EVs. In terms of EV technology, a simple increase of battery size does not necessarily mean continuous increase in flexibility from EVs, increase in revenues for the charging station operator and EV bills savings. $CO_2$eq emissions remain constant in the two G2V cases whereas emissions decrease in the V2G near home case, and emissions slightly increase in the V2G work case. Bidding capacity increases in the V2G cases, however biggest changes in capacity are observed between 12 to 32 kWh battery size.

The sensitivity analysis of charging rate of EVs is presented in Figure 5.7. The impact on the charging operator revenues observed at the top left graph indicate a significant increase up to about 50 kW of charging rate for the two V2G cases. There isn't impact on the two G2V cases as it is not possible to use discharging of EVs as charging rate increases, and therefore EV charging schedules remain the same. EV bills (utilities) also increase with charging rating specially before 50 kW rating. In

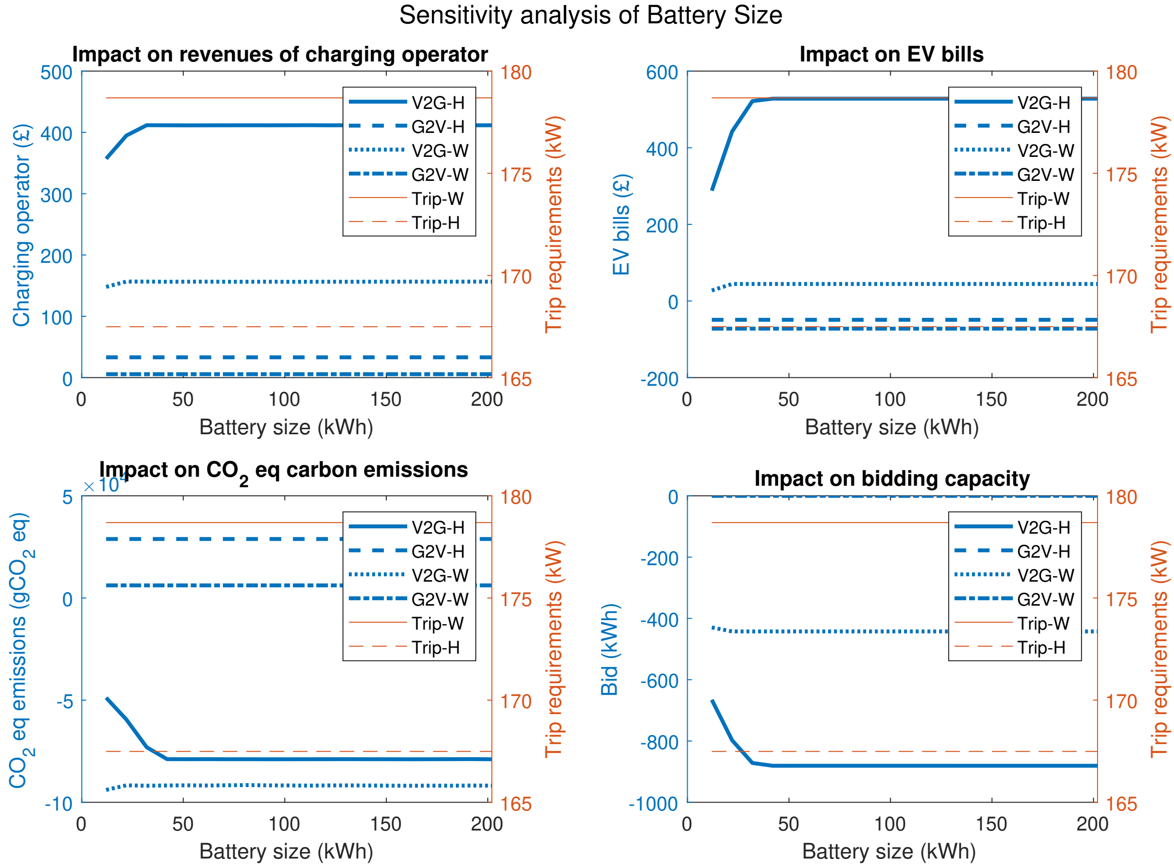


Figure 5.6: Sensitivity analysis of EV Battery Size with case scenarios with nomenclature of: EV Technology (V2G-bidirectional/ G2V-unidirectional) - charging location (W-work/ H-near home) and Trip Requirements (Trip) - charging location (W-work/ H-near home).

contrast to the charging operator utilities and EV bills of the sensitivity analysis of battery size, charging rating shows bigger impact on money as more flexibility is obtained in the V2G cases. In terms of reduction of $CO_2$eq emissions and increase bidding capacity as charging rate increases, the V2G home shows the best results followed also by the V2G case at work location.

To finish with the sensitivity analysis of EV parameters, Figure 5.8 shows the results obtained when reducing EV availability, that is hours reduced from both stochastic arrival and departures of EVs. As trip requirements are adjusted to match charging rate limitations with time available for charging, trips for the work case scenario are reduced to near zero after reducing 11 hours to EVs availability. On the other hand,

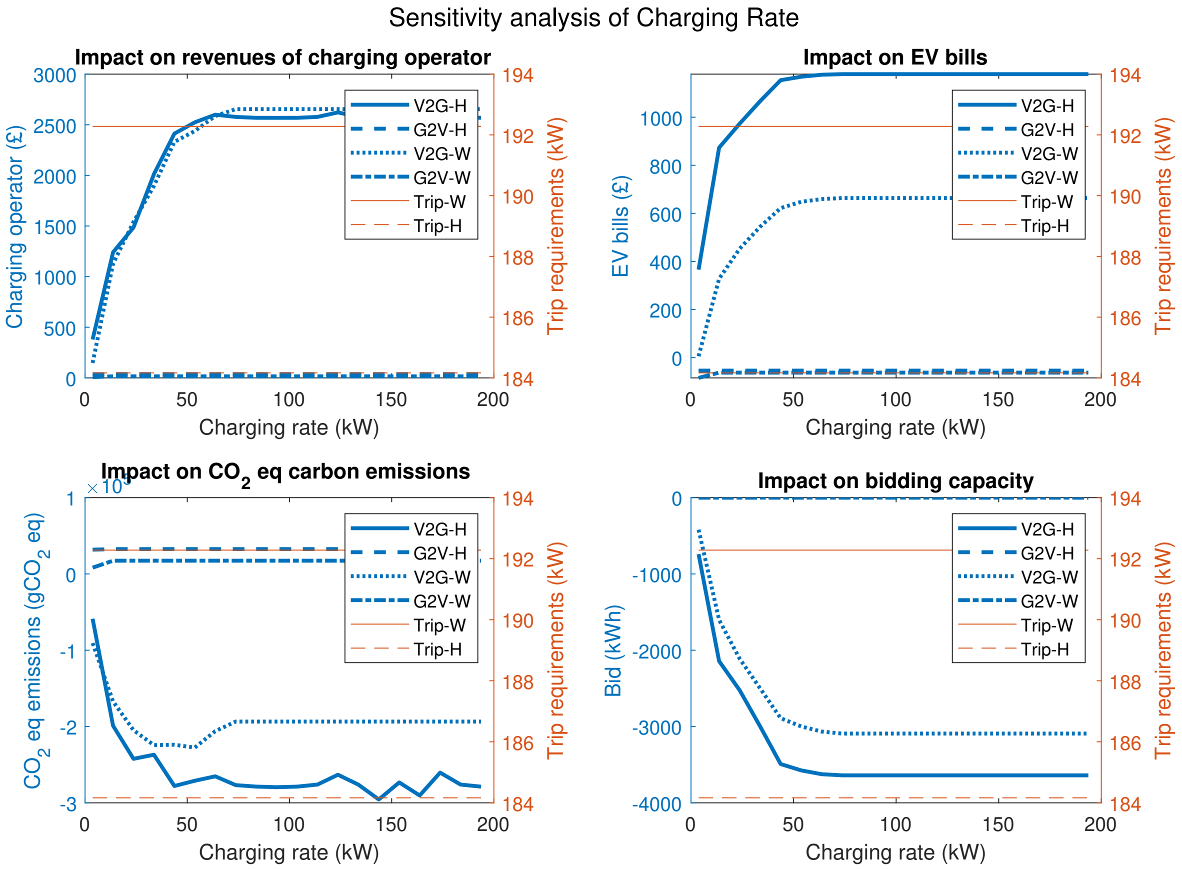


Figure 5.7: Sensitivity analysis of EV Charging Rate with case scenarios with nomenclature of: EV Technology (V2G-bidirectional/ G2V-unidirectional) - charging location (W-work/ H-near home) and Trip Requirements (Trip) - charging location (W-work/ H-near home).

trips for near home location decrease as EV hours of availability are reduced. This reduction in trips and EV availability reflect that case scenarios for revenues for the charging operator and EV bills get close to zero after reduction of 11 hours. This same pattern is followed by the impact on $CO_2$eq emissions and bidding capacity. By contrast, the reduction in hours for the near home location allows EV users and the charging station operator to have some utilities for both the V2G and G2V cases. Meanwhile, EV bills are positive, meaning EVs receive utilities, only in the V2G at near home case. In the G2V at near home case, EVs receive utilities and have costs after a reduction in availability of 16 hours. The impact of $CO_2$eq emissions at near home location differs with V2G and G2V technology; with V2G technology

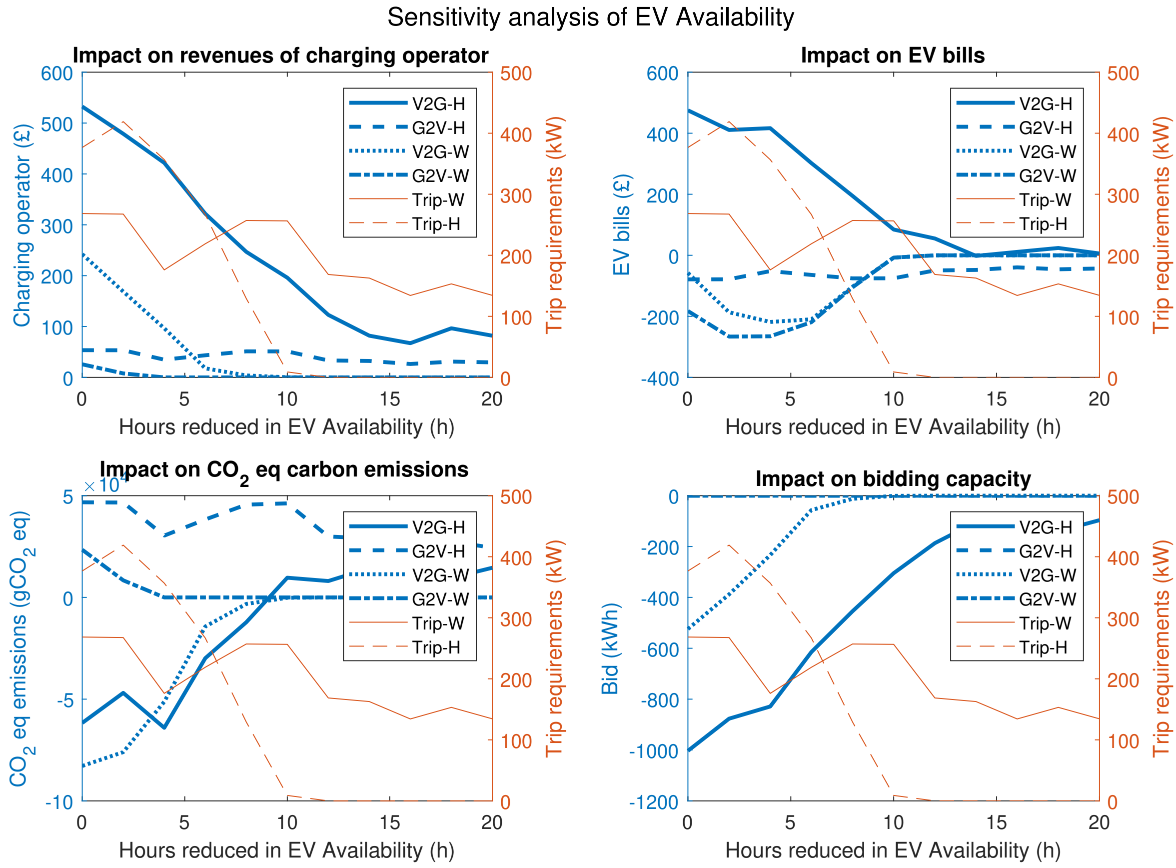


Figure 5.8: Sensitivity analysis of EV Availability with case scenarios with nomenclature of: EV Technology (V2G-bidirectional/ G2V-unidirectional) - charging location (W-work/ H-near home) and Trip Requirements (Trip) - charging location (W-work/ H-near home).

$CO_2$eq emissions increase with reduction of availability whereas with G2V technology emissions do not reduce significantly. Finally, bidding capacity reaches zero starting with the V2G at work location and then followed by the V2G at near home location.

## 5.4 Chapter Remarks

### 5.4.1 Discussions

The sensitivity analysis presented in this Chapter uses the mathematical modeling of charging station operator with solar panels available for charging EVs. Thus, the limitations of the analysis are presented also in the formulation of the model. For instance, trip requirements were adjusted to comply with charging restrictions and battery size limitations, thus the difference between the original trip requirements and the adjusted requirements was not analyzed. A slack variable in the trip requirement could be implemented in the future to consider the differences for instance on customer satisfaction for instance when reducing trip requirements. Another limitation of the sensitivity analysis is that the parameters were analyzed separately for practical purposes, however there are variables that together can improve the performance of the results, for example a combination of increase in battery size and charging rate.

The parameters proposed in the sensitivity analysis of this Chapter were selected as potential improvement indicators in terms of utilities, $CO_2$eq emissions and bidding capacity. However, the implementation of further changes to the parameters should be carefully considered. In the case of trip requirements and initial state of charge, EV charging control could set the right values for both parameters depending on the desired impact on the indicators discussed. Number of EVs and solar panels of the charging station could give a guidance in terms of impact on day to day operation depending on the size of a charging station, however other costs should also be considered when making an economic analysis. Moving now to EV battery size and charging rate, as these are parameters defined by the original equipment manufacturers, this is hard to manipulate from the charging operator side, but EV charging operators can take advantage and make predictions of biding capacity and potential of EVs as technology improves. Finally, EV availability depends on users behavior, however the charging station operator could incentivise users availability and have better prediction of arrivals and departures for planning purposes.

### 5.4.2 Conclusions

This Chapter presented a sensitivity analysis for selected parameters that could be controlled by the charging operator and define the size of a charging station, and that are EV related parameters depending on EV behavior and technology. Greater impacts in terms of increasing revenues for the charging station operator, EV utilities and reduction of $CO_2$eq emissions and bidding capacity were obtained with increasing charging rate of EVs and of the charging station pole, however it is important to mention that grid reinforcement costs and other initial investment costs associated with the charging station are not considered. Greatest reduction in revenues for the charging station operator, EV utilities, reduction of $CO_2$eq emissions and bidding capacity was obtained with a reduction in EV charging availability at the charging station, as a result of not being able to use EVs for either charging or for providing flexibility services.

Future directions of research with the use of the model used for the sensitivity analysis in this Chapter include sizing of a charging station that could consider initial investment of a charging station and solar panels, operational costs and potential connection costs for installing EV charging poles in a specific location. This sizing model could also include a sensitivity analysis with varying charging poles, solar panels depending on area restrictions and potential demand of EVs. Another analysis that could be used with the model could also consider the best location for a charging station that can ensure maximisation of utilisation of charging stations and inclusivity of deployed charging infrastructure for EV users. The model used for the sensitivity analysis can also be used to predict better EV arrivals and departures as well as control improvement for trip requirements and EV state of charge, specially in a case where an EV aggregator engages with EVs to provide flexibility in exchange of management of EV charging.

# Chapter 6

# Conclusions

This final Chapter presents the general contributions of this Thesis in each Chapter with its corresponding most relevant results to summarize content and analysis discussed previously. Future research directions are also presented in order to provide insights about the work that can be further developed or complement the work already completed in this thesis.

## 6.1 Final conclusions

This Thesis provided significant contributions to knowledge to the area of demand response pricing schemes and EV charging to reduce $CO_2$eq carbon emissions. First, Chapter 3 provided a data driven approach to estimate time of use pricing based on historical EV charging response to price in a solar V2G/G2V charging station. The proposed pricing scheme included a bi-level optimisation where pricing was optimised considering maximisation of revenues for the charging station operator and expected EV charging response to price from EV users. Then, an EV charging bidding optimisation model was proposed considering stochastic behavior of EVs such as: arrivals, departures, initial state of charge and trip requirements. The pricing scheme proposed in Chapter 3 also demonstrated how pricing can influence driving behavior during balancing services timings and it solved the pricing dilemma for setting profitable pricing for EV charging and for auctions in energy markets. EV charging response to price and bidding schedules were estimated with the EV charging optimisation model where users demonstrated engagement in participating in flexibility services offered to the grid. After evaluating the model in different scenarios of charging technology and EV driver behavior, for the V2G or bidirectional scenarios, rapid charging with the more inelastic curve was the case with greater revenues. For the G2V or unidirectional scenarios, the fast charging 2 with the more inelastic curve was the case with greater revenues.

Having described the proposed model in Chapter 3, to reiterate the objectives and contributions, in summary Chapter 3 addressed ***Objective 1*** and ***Objective 2*** of this thesis which were stated in the Introduction section of this thesis. ***Objective 1*** was to design a pricing scheme that can influence EV drivers to participate in balancing services. The contributions related to this objective were: new dynamic time of use pricing scheme based on inverse demand curve that ensures economical and EV user engaging behavior, demand responsive pricing scheme solves pricing dilemma of prices for EV users and prices for participation in balancing services. ***Objective 2*** was to design an EV charging control planning scheme to account for bidding and EV charging. The contributions related to this objective were: bi-level optimisation with pricing that feeds into EV charging control optimisation that produces bidding and charging schedules, this EV charging control optimisation used for computing EV charging schedules is capable of modelling stochastic EV charging behavior and both V2G, bidirectional or vehicle to grid power flow, and G2V, unidirectional or grid to vehicle power flow technologies.

Chapter 4 presented a contribution to the area of fairness in multi-objective optimisation for EV charging in order to reduce $CO_2$eq emissions. The multi-objective optimisation considered three stakeholders: EV users (who are impacted by carbon taxes in energy generation), a carbon regulator (that penalises charging during timings whose grid carbon factor is above nominal carbon values), and a charging operator (that intends to participate in carbon trading markets). A weight was assigned to each goal in order to evaluate the influence over each goal in EV charging schedules. To evaluate fairness between all weights assigned to each objective function, a genetic algorithm known by the research community as NSGA-II was adapted to find non dominated solutions that formed a pareto frontier set. To select solutions from the pareto frontier set, two methods were proposed to either obtain a most preferred ranked solution (considering stakeholders perspective) and a green solution (that minimised $CO_2$eq emissions). After comparing EV charging locations at residential areas (near home) and charging at work, the fairest solution for the work and near home case assigned the highest weight factor to the objective function of EV users, followed by the charging operator and the carbon regulator. In terms of the greenest solutions, the near home case had same priority of weight assignation to the objective functions when comparing to the fairest solution, whereas the work case assigned a higher weight to the charging operator followed by EV users and the carbon regulator.

Having described the proposed model in Chapter 4, to reiterate the objectives and contributions, in summary Chapter 4 addressed ***Objective 3*** and ***Objective 4*** which were stated in the Introduction section of this thesis. ***Objective 3*** was to design a control scheme for EV charging to reduce carbon emissions. The contributions presented in this Chapter related to this objective were: new formulation of smart EV charging to reduce carbon emissions that includes goal of EV users, charging operator and carbon regulator, weights are assigned to each goal as design optimisation variables. ***Objective 4*** was to design a multi-objective optimisation approach to ensure fairness between all objectives and evaluate the trade-offs between all stakeholders. To address this goal, this Chapter presented the following contributions: linear programming formulation integration with genetic algorithm to ensure fairness and reduction of carbon emissions. For this integration, two non-dominated criteria is proposed: best ranked solution and minimisation of carbon emissions.

Finally, Chapter 5 presented a numerical assessment with a sensitivity analysis of EV charging parameters to find improvement research opportunities and limitations using the models proposed in Chapter 3 and Chapter 4. The sensitivity analysis was divided into two main categories of selected charging station parameters: those related to control and sizing of the charging station and those related to EV driving behavior and electric vehicle technology. For practical purposes, the model used to perform the sensitivity analysis was selected from the pricing scheme that included carbon taxes from Chapter 4 and the EV charging optimisation used in Chapter 3. The best results in terms of performance indicators such as revenues for the charging operator, utilities for EV users, minimisation of carbon emissions and bidding capacity for carbon markets were obtained when increasing EV charging ratings. In contrast, EV charging availability was the parameter with greater negative impact (reduction of revenues) in overall performance indicators.

Having described the proposed model in Chapter 5, to reiterate the objectives and contributions, in summary Chapter 5 addressed ***Objective 5*** described in the Introduction section of this thesis. ***Objective 5*** was to analyze what parameters can improve the performance of a charging station operator stakeholder. The contribution in this Chapter related to this objective was the strategic assessment, made with sensitivity analysis using one factor at a time method, to evaluate selected parameter inputs measured by performance indicators of $CO_2$eq emissions, bidding capacity to be used in market auctions, revenues and costs for both EV users and the charging operator.

## 6.2 Future Research Work

### 6.2.1 Pricing Competition

The pricing scheme proposed in Chapter 3 proposed a data driven price optimisation, where formulation includes the maximisation of revenues and response of EVs to price over time using historical charging demand. Competition is indirectly included in the historical demand of EVs, for instance if users choose to charge in another charging stations nearby with a cheaper price, this change in demand can be reflected after estimating new historical responses to price. However, a real time response to competition is not considered. Future research in competition could include expected pricing response from other charging stations for instance using expected Bertrand competition where it is assumed that EV users with known information of charging stations are more likely to choose the charging station with the cheapest charging bill. Competition modelling could also be optimised in the case where the charging operator owns several charging stations in the same area, Cournot competition formulation could be used in order to optimise optimum bidding quantity from EV to use for balancing services in order to predict price. Another consideration of competition could include expected pricing from other bidding competitors based on capacity, price and estimations of performance response to balancing services.

### 6.2.2 Pricing Differentiation

Chapter 3 proposed solving the pricing dilemma of how to set prices for EV charging users and for energy auctions when using EVs as flexibility assets. Future research work to improve revenues for EV charging operators could include other pricing options where users can be classified based on willingness to pay for specific charging services. Pricing diversification could include different pricing for premium or basic users that are willing to pay more for specific charging station options. In order to estimate pricing differentiation using historical responses to price in time using inverse demand curve, different pricing can include levels of elasticity in time and preferences for charging of users with regard to different parameters such as number of charging times in a week and unlocking specific charging locations.

### 6.2.3 EV Charging Welfare

Pricing strategies were estimated to maximise revenues as profitability is one of the main barriers to commercialise V2G charging technology for balancing services, however pricing fairness was not considered. A fairness equilibrium to reach a balance between social welfare and maximisation of revenues for the charging station operator, is an addition to the pricing scheme that could be further explored in the future. A method that could be used for future research could contemplate non-cooperative game theory formulations with Nash Equilibrium. In terms of further additions to the EV charging optimisation model, further improvements could include charging priority in order to manage charging ratings considering grid topology and transformer constraints, where user satisfaction levels could be used to balance not reaching to specific trip requirements in a charging location if necessary.

### 6.2.4 Markets to Integrate EVs

In this Thesis, EVs' flexibility was studied to reflect EVs response to price in charging schedules that could be used for incorporating EVs energy flexibility in balancing services. The EV charging optimisation for estimating EV charging schedules considered granularity on hourly periods, however additional considerations to the charging schedules could include reduced granularity of data to test with 30 min periods for instance for the wholesale market in the UK. In addition, EV charging control could also consider real time response to regulation signals coming from the transmission system operator in the UK (National Grid) or distribution system operators that could use either power or voltage deviation signals. Finally, another addition to the control for EV charging could include inclusion of EVs in peer energy trading using decentralised charging control algorithms.

### 6.2.5 Accuracy of Charging Data

In this Thesis, inputs for estimating EV charging optimisation used data from: distribution fitting indicating EV driver behavior (EV arrivals and departures), empirical distributions to estimate trip and initial state of charge parameters, linear estimation for EVs driver response to price and average hourly solar power. These inputs are fixed and therefore, are practical for simulation purposes, but having accurate information to be used real case scenarios can be critical to estimate precise bidding capacity and expected profits. In order to estimate accurate prediction, more advanced methods can be used such as ARIMA and artificial neural networks. Non linear estimations of charging demand response to price could be also explored, where estimations could include demand and price relationships in smart grids, for instance sigmoid functions have been commonly modelled in models closer to real time settings.

# Appendix

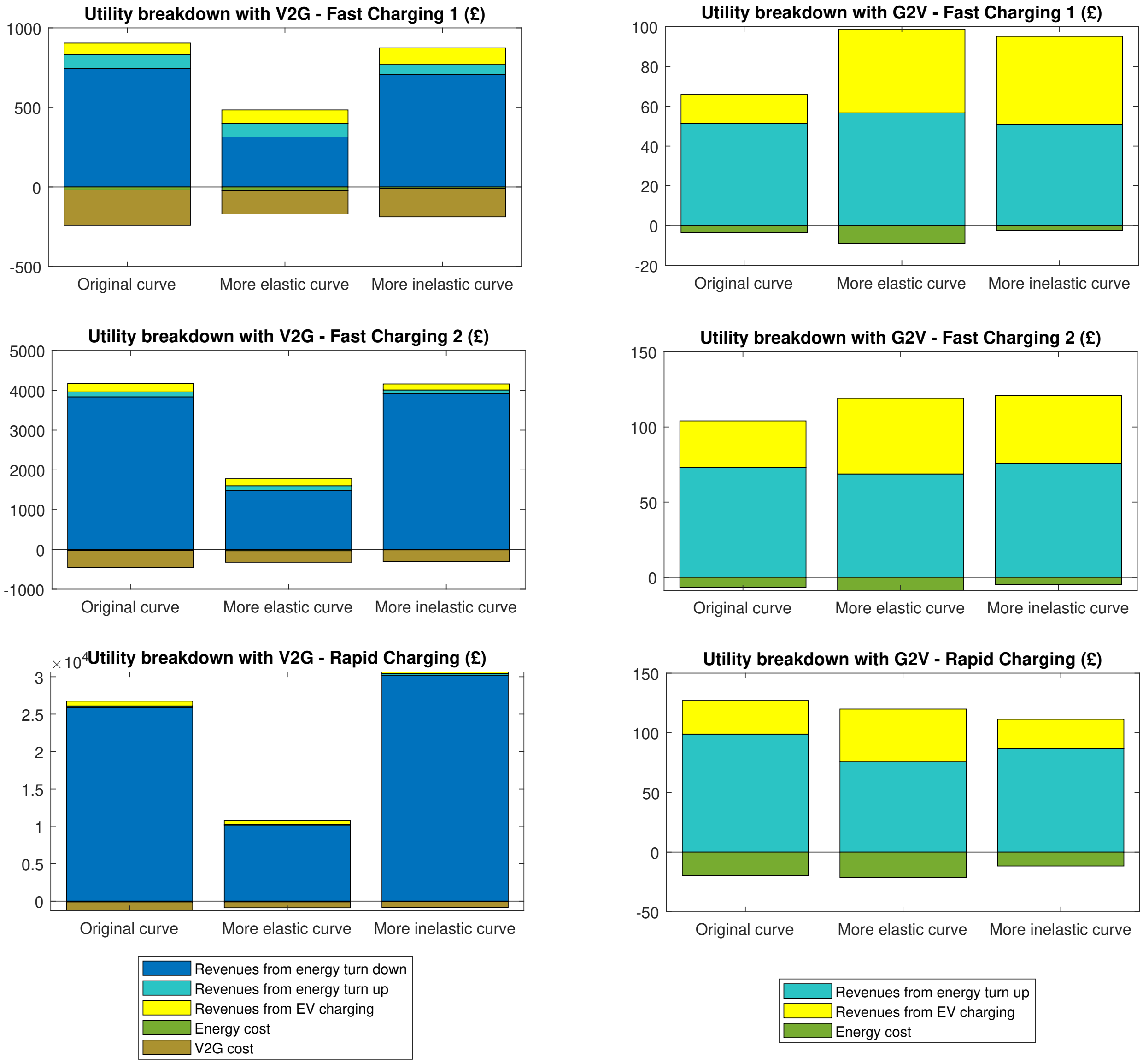


Figure 1: Net profits/utilities breakdown with pricing using the three inverse demand curves and charging cases.

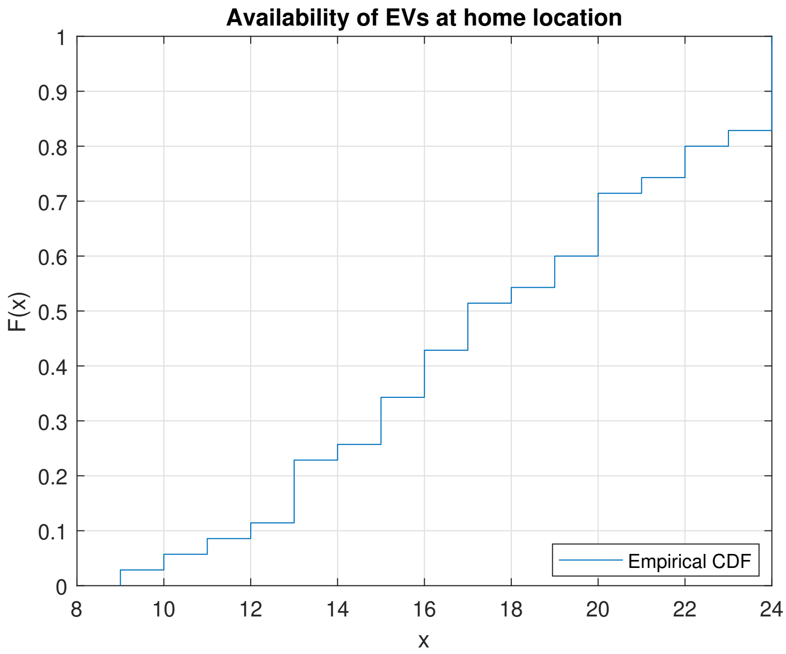


Figure 2: Empirical CDF for availability of EVs at home location considering arrival and departures during a day.

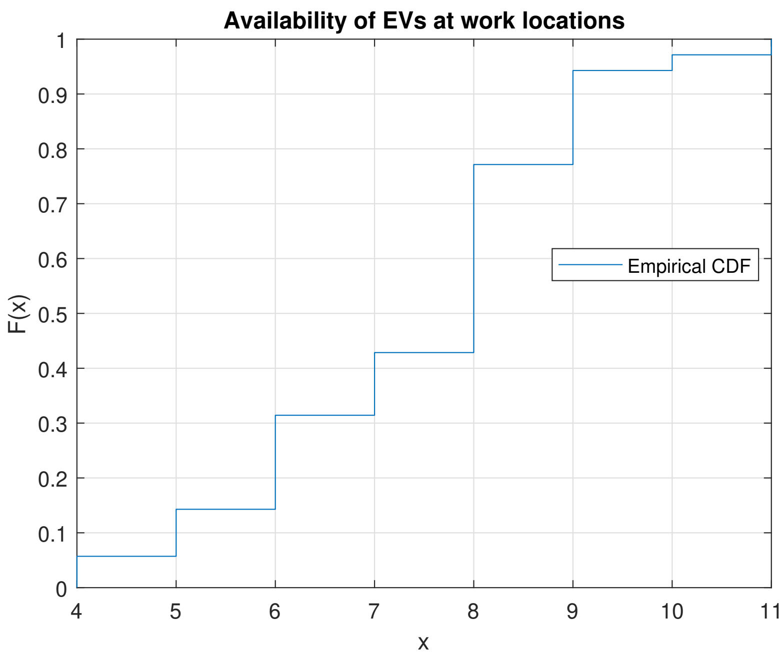


Figure 3: Empirical CDF for availability of EVs at work location considering arrival and departures during a day.

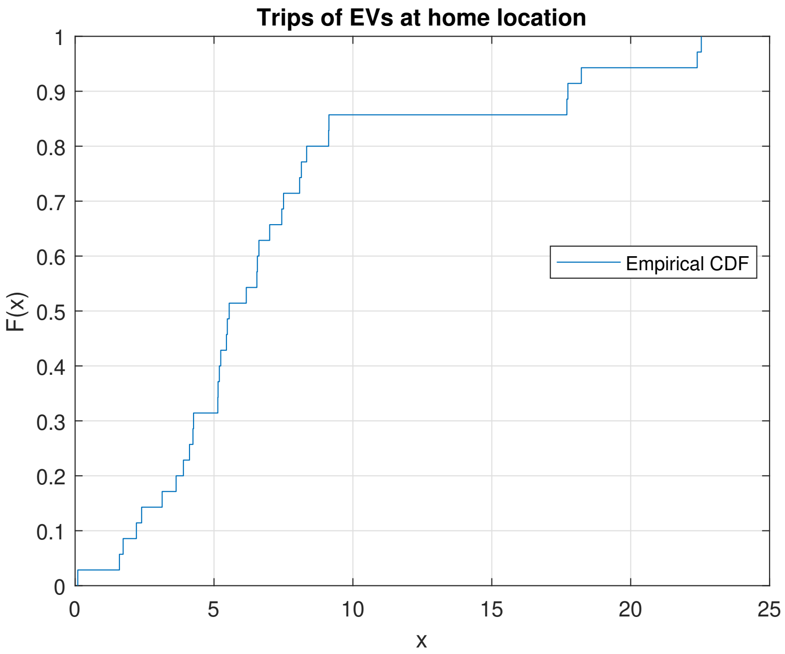


Figure 4: Empirical CDF for trip requirements of EVs at home location.

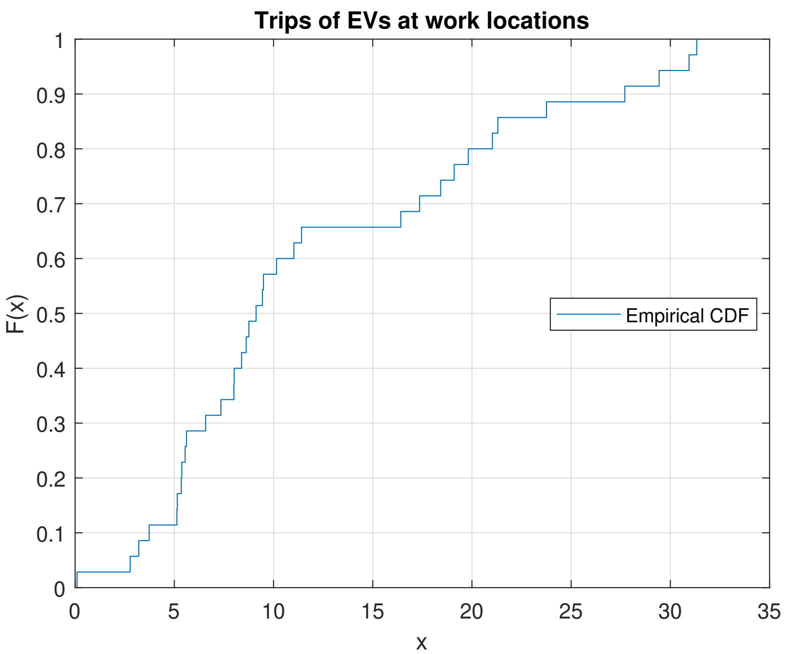


Figure 5: Empirical CDF for trip requirements of EVs at work location.

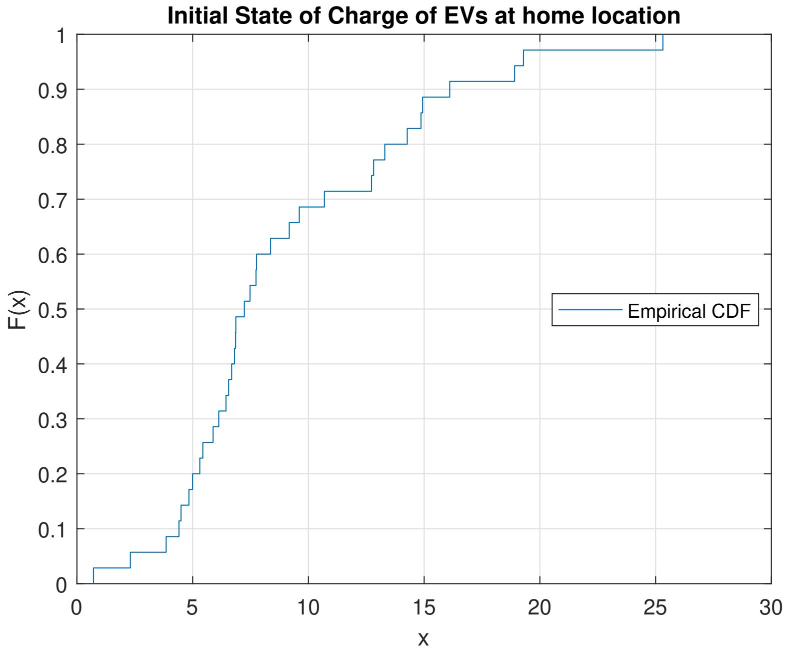


Figure 6: Empirical CDF for initial battery state of charge of EVs at home location.

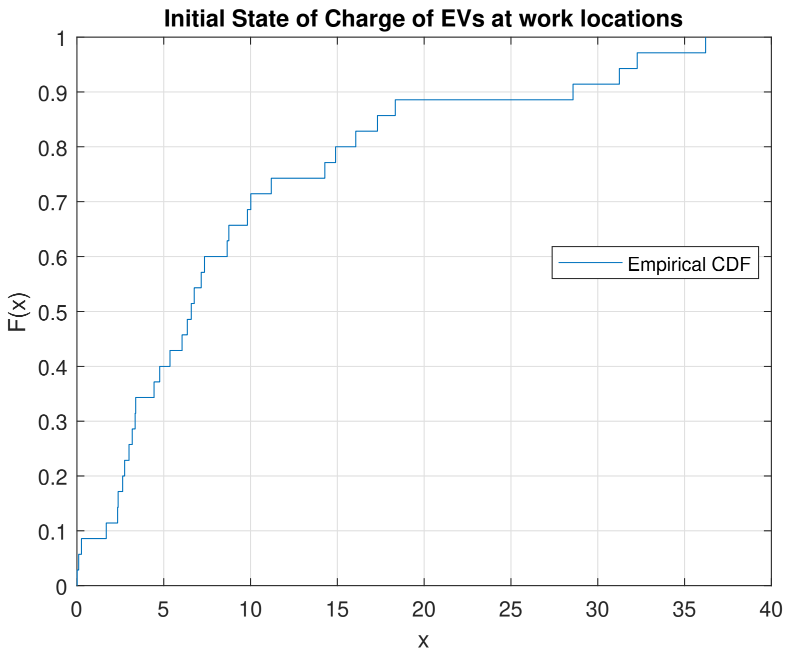


Figure 7: Empirical CDF for initial battery state of charge of EVs at work location.

# References


[1] " Climate Change: Global Temperature." Climate.gov. Accessed: March 27, 2022. [Online]. Available: https://parker-project.com/https://nuvve.com/2019/01/15/the-match-has-been-made-evs-are-ready-to-support-the-electricity-grid/

[2] "Transport Improving the sustainability of passenger and freight transport." iea.org . Accessed: August 13, 2022. [Online]. Available: https://www.iea.org/topics/transport

[3] "COP26 declaration on accelerating the transition to 100% zero emission cars and vans." iea.org . Accessed: August 13, 2022. [Online]. Available: https://www.gov.uk/government/publications/cop26-declaration-zero-emission-cars-and-vans/cop26-declaration-on-accelerating-the-transition-to-100-zero-emission-cars-and-vans

[4] " UK enshrines new target in law to slash emissions by 78% by 2035 ." GOV.UK . Accessed: March 27, 2022. [Online]. Available: https://www.gov.uk/government/news/uk-enshrines-new-target-in-law-to-slash-emissions-by-78-by-2035

[5] "The Ten Point Plan for a Green Industrial Revolution," HM Government, November, 2020. Accessed: March 27, 2022. [Online]. Available: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/936567/10_POINT_PLAN_BOOKLET.pdf

[6] "Mexico Energy Outlook," IEA , 2016. Accessed: March 27, 2022. [Online]. Available: https://iea.blob.core.windows.net/assets/e911d7c8-955a-4495-ace0-da85ac4484f9/MexicoEnergyOutlook.pdf

[7] "Firman AMIA y CFE convenio para promover el uso de autos eléctricos e híbridos," PortalAutomotriz.com , April 13, 2016. Accessed: March 27, 2022. [Online]. Available: https://www.portalautomotriz.com/noticias/automotriz/firman-amia-y-cfe-convenio-para-promover-el-uso-de-autos-electricos-e-hibridos

[8] "Energy Policies Beyond IEA Countries: Mexico 2017," IEA , 2017. Accessed: March 27, 2022. [Online]. Available: https://www.iea.org/reports/energy-policies-beyond-iea-countries-mexico-2017,

[9] " Generation by Fuel Type," Elexon, March 27, 2022. Accessed: March 27, 2022. [Online]. Available: https://www.bmreports.com/bmrs/?q=generation/fueltype/current

[10] Z. Ding, F. Zhu, Y. Wang, Y. Lu, and L. Zhang, "Flexible demand resource pricing scheme: A stochastic benefit-sharing approach," *IEEE Transactions on Industry Applications*, vol. 55, no. 6, pp. 5554–5563, 2019.

[11] D. Muthirayan, D. Kalathil, K. Poolla, and P. Varaiya, "Mechanism design for demand response programs," *IEEE Transactions on Smart Grid*, vol. 11, no. 1, pp. 61–73, 2020.

[12] UNFCCC, "THE PARIS AGREEMENT," https://bigpicture.unfccc.int/404.htmlcontent-the-paris-agreemen, 2018-05-10.

[13] Parliament of the United Kingdom, "Climate Change Act 2008," p. 103, 2008. [Online]. Available: https://www.legislation.gov.uk/ukpga/2008/27/pdfs/ukpga{_}20080027{_}en.pdf

[14] International Energy Agency, "Energy Policies Beyond IEA Countries: Mexico 2017," Tech. Rep., 2017. [Online].

Available: https://www.iea.org/publications/freepublications/publication/EnergyPoliciesBeyondIEACountriesMexico2017.pdf

[15] ——, "TRANSPORT, ENERGY AND CO2," France, Tech. Rep., 2009. [Online]. Available: https://www.iea.org/publications/freepublications/publication/transport2009.pdf

[16] C. T. Rim and C. Mi, "Introduction to Electric Vehicles (EVs)," in *Wireless Power Transfer for Electric Vehicles and Mobile Devices*. Chichester, UK: John Wiley & Sons, Ltd, jun 2017, pp. 43–49. [Online]. Available: http://doi.wiley.com/10.1002/9781119329084.ch3

[17] S. Impram, S. Varbak Nese, and B. Oral, "Challenges of renewable energy penetration on power system flexibility: A survey," *Energy Strategy Reviews*, vol. 31, p. 100539, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2211467X20300924

[18] N. M. Haegel, R. Margolis, T. Buonassisi, D. Feldman, A. Froitzheim, R. Garabedian, M. Green, S. Glunz, H.-M. Henning, B. Holder, I. Kaizuka, B. Kroposki, K. Matsubara, S. Niki, K. Sakurai, R. A. Schindler, W. Tumas, E. R. Weber, G. Wilson, M. Woodhouse, and S. Kurtz, "Terawatt-scale photovoltaics: Trajectories and challenges." *Science (New York, N.Y.)*, vol. 356, no. 6334, pp. 141–143, apr 2017. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/28408563

[19] W. Shuai, P. Maillé, and A. Pelov, "Charging electric vehicles in the smart city: A survey of economy-driven approaches," *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 8, pp. 2089–2106, Aug 2016.

[20] Q. Wang, X. Liu, J. Du, and F. Kong, "Smart charging for electric vehicles: A survey from the algorithmic perspective," *IEEE Communications Surveys Tutorials*, vol. 18, no. 2, pp. 1500–1517, Secondquarter 2016.

[21] E. S. Rigas, S. D. Ramchurn, and N. Bassiliades, “Managing Electric Vehicles in the Smart Grid Using Artificial Intelligence: A Survey,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 4, pp. 1619–1635, aug 2015. [Online]. Available: http://ieeexplore.ieee.org/document/7000557/

[22] Z. Ding, Y. Lu, L. Zhang, W.-J. Lee, and D. Chen, “A Stochastic Resource-Planning Scheme for PHEV Charging Station Considering Energy Portfolio Optimization and Price-Responsive Demand,” *IEEE Transactions on Industry Applications*, vol. 54, no. 6, pp. 5590–5598, nov 2018. [Online]. Available: https://ieeexplore.ieee.org/document/8399523/

[23] A. Gil, P. Sauras-Perez, and J. Taiber, “Communication requirements for Dynamic Wireless Power Transfer for battery electric vehicles,” in *2014 IEEE International Electric Vehicle Conference (IEVC)*. IEEE, dec 2014, pp. 1–7. [Online]. Available: http://ieeexplore.ieee.org/document/7056176/

[24] Transport Research Laboratory (TRL), “Feasibility study: Powering electric vehicles on England’s major roads,” Tech. Rep., 2015. [Online]. Available: http://assets.highways.gov.uk/specialist-information/knowledge-compendium/2014-2015/Feasibility+study+Powering+electric+vehicles+on+Englands+major+roads.pdf

[25] A. Ahmad, M. S. Alam, and R. Chabaan, “A Comprehensive Review of Wireless Charging Technologies for Electric Vehicles,” *IEEE Transactions on Transportation Electrification*, vol. 4, no. 1, pp. 38–63, mar 2018. [Online]. Available: http://ieeexplore.ieee.org/document/8101562/

[26] O. Veneri, L. Ferraro, C. Capasso, and D. Iannuzzi, “Charging infrastructures for EV: Overview of technologies and issues,” in *2012 Electrical Systems for Aircraft, Railway and Ship Propulsion*. IEEE, oct 2012, pp. 1–6. [Online]. Available: http://ieeexplore.ieee.org/document/6387434/

[27] A. Khaligh and S. Dusmez, “Comprehensive Topological Analysis of

Conductive and Inductive Charging Solutions for Plug-In Electric Vehicles," *IEEE Transactions on Vehicular Technology*, vol. 61, no. 8, pp. 3475–3489, oct 2012. [Online]. Available: http://ieeexplore.ieee.org/document/6266761/

[28] B. Esteban, M. Sid-Ahmed, and N. C. Kar, "A comparative study of power supply architectures in wireless ev charging systems," *IEEE Transactions on Power Electronics*, vol. 30, no. 11, pp. 6408–6422, Nov 2015.

[29] D. Nicolaides, R. McMahon, D. Cebon, and J. Miles, "A National Power Infrastructure for Charge-on-the-Move: An Appraisal for Great Britain," *IEEE Systems Journal*, pp. 1–9, 2018. [Online]. Available: http://ieeexplore.ieee.org/document/8276239/

[30] Siqi Li and C. C. Mi, "Wireless Power Transfer for Electric Vehicle Applications," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 3, no. 1, pp. 4–17, mar 2015. [Online]. Available: http://ieeexplore.ieee.org/document/6804648/

[31] "The NORWEGIAN American." [Online]. Available: https://www.norwegianamerican.com/research/norway-opens-largest-ev-charge-station/

[32] F. Musavi, M. Edington, and W. Eberle, "Wireless power transfer: A survey of EV battery charging technologies," in *2012 IEEE Energy Conversion Congress and Exposition (ECCE)*. IEEE, sep 2012, pp. 1804–1810. [Online]. Available: http://ieeexplore.ieee.org/document/6342593/

[33] X. Mou and H. Sun, "Wireless Power Transfer: Survey and Roadmap," in *2015 IEEE 81st Vehicular Technology Conference (VTC Spring)*. IEEE, may 2015, pp. 1–5. [Online]. Available: http://ieeexplore.ieee.org/document/7146165/

[34] T. Theodoropoulos, Y. Damousis, A. Amditis, G. Karaseitanidis, and P. Guglielmi, "Smart grid architectures for dynamic wireless ev charging," in *Mediterranean Conference on Power Generation, Transmission, Distribution and Energy Conversion (MedPower 2016)*, Nov 2016, pp. 1–7.

[35] S. Jeong, Y. J. Jang, and D. Kum, “Economic Analysis of the Dynamic Charging Electric Vehicle,” *IEEE Transactions on Power Electronics*, vol. 30, no. 11, pp. 6368–6377, nov 2015. [Online]. Available: http://ieeexplore.ieee.org/document/7089287/

[36] "EV Charging Connector Types and Speeds." podPOINT. Accessed: March 11, 2022. [Online]. Available: https://pod-point.com/guides/driver/ev-connector-types-speed

[37] "EV Charging Speeds Explained: How Much Power Are You Really Getting?." mer. Accessed: March 11, 2022. [Online]. Available: https://uk.mer.eco/news/ev-charging-speeds-explained-how-much-power-are-you-really-getting/

[38] M. C. Maurici and J. M. Frigola, “Electric vehicle user profiles for aggregated flexibility planning,” in *2021 IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe)*, 2021, pp. 1–5.

[39] H. Turker and S. Bacha, “Optimal minimization of plug-in electric vehicle charging cost with vehicle-to-home and vehicle-to-grid concepts,” *IEEE Transactions on Vehicular Technology*, vol. 67, no. 11, pp. 10 281–10 292, 2018.

[40] M. Kumar, S. Vyas, and A. Datta, “A review on integration of electric vehicles into a smart power grid and vehicle-to-grid impacts,” in *2019 8th International Conference on Power Systems (ICPS)*, 2019, pp. 1–5.

[41] M. Yilmaz and P. T. Krein, “Review of the impact of vehicle-to-grid technologies on distribution systems and utility interfaces,” *IEEE Transactions on Power Electronics*, vol. 28, no. 12, pp. 5673–5689, 2013.

[42] A. Thingvad, L. Calearo, P. B. Andersen, and M. Marinelli, “Empirical capacity measurements of electric vehicles subject to battery degradation from v2g services,” *IEEE Transactions on Vehicular Technology*, vol. 70, no. 8, pp. 7547–7557, 2021.

[43] J. S. Vardakas, N. Zorba, and C. V. Verikoukis, “A Survey on Demand Response Programs in Smart Grids: Pricing Methods and Optimization Algorithms,” *IEEE Communications Surveys & Tutorials*, vol. 17, no. 1, pp. 152–178, 2015. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6861959

[44] N. G. Paterakis, O. Erdinç, and J. P. Catalão, “An overview of Demand Response: Key-elements and international experience,” *Renewable and Sustainable Energy Reviews*, vol. 69, pp. 871–891, mar 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032116308966

[45] W. Saad, Z. Han, H. Poor, and T. Basar, “Game-Theoretic Methods for the Smart Grid: An Overview of Microgrid Systems, Demand-Side Management, and Smart Grid Communications,” *IEEE Signal Processing Magazine*, vol. 29, no. 5, pp. 86–105, sep 2012. [Online]. Available: http://ieeexplore.ieee.org/document/6279592/

[46] H. Humfrey and H. Sun, “Dynamic Charging of EVs Integrating Renewable Energy: A Multi-Objective Optimisation Problem,” *IET Smart Grid*, vol. 2, no. 2, pp. 250–259, 2019.

[47] S.-G. Yoon, Y.-J. Choi, J.-K. Park, and S. Bahk, “Stackelberg-Game-Based Demand Response for At-Home Electric Vehicle Charging,” *IEEE Transactions on Vehicular Technology*, vol. 65, no. 6, pp. 4172–4184, jun 2016. [Online]. Available: http://ieeexplore.ieee.org/document/7116607/

[48] A.-H. Mohsenian-Rad, V. W. S. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, “Autonomous Demand-Side Management Based on Game-Theoretic Energy Consumption Scheduling for the Future Smart Grid,” *IEEE Transactions on Smart Grid*, vol. 1, no. 3, pp. 320–331, dec 2010. [Online]. Available: http://ieeexplore.ieee.org/document/5628271/

[49] M. H. K. Tushar, A. W. Zeineddine, and C. Assi, “Demand-Side

Management by Regulating Charging and Discharging of the EV, ESS, and Utilizing Renewable Energy," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 1, pp. 117–126, jan 2018. [Online]. Available: http://ieeexplore.ieee.org/document/8048016/

[50] E. L. Karfopoulos and N. D. Hatziargyriou, "A Multi-Agent System for Controlled Charging of a Large Population of Electric Vehicles," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 1196–1204, may 2013. [Online]. Available: http://ieeexplore.ieee.org/document/6299001/

[51] Changsun Ahn, Chiao-Ting Li, and Huei Peng, "Decentralized charging algorithm for electrified vehicles connected to smart grid," in *Proceedings of the 2011 American Control Conference.* IEEE, jun 2011, pp. 3924–3929. [Online]. Available: http://ieeexplore.ieee.org/document/5990895/

[52] S. Shao, W. Guan, and J. Bi, "Electric vehicle-routing problem with charging demands and energy consumption," *IET Intelligent Transport Systems*, vol. 12, no. 3, pp. 202–212, apr 2018. [Online]. Available: http://digital-library.theiet.org/content/journals/10.1049/iet-its.2017.0008

[53] S. Storandt and Sabine, "Quick and energy-efficient routes," in *Proceedings of the 5th ACM SIGSPATIAL International Workshop on Computational Transportation Science - IWCTS '12.* New York, New York, USA: ACM Press, 2012, pp. 20–25. [Online]. Available: http://dl.acm.org/citation.cfm?doid=2442942.2442947

[54] E. S. Rigas, S. D. Ramchurn, N. Bassiliades, and G. Koutitas, "Congestion management for urban EV charging systems," in *2013 IEEE International Conference on Smart Grid Communications (SmartGridComm).* IEEE, oct 2013, pp. 121–126. [Online]. Available: http://ieeexplore.ieee.org/document/6687944/

[55] T. V. Theodoropoulos, I. G. Damousis, E. Portouli, A. J. Amditis, N. E. Sayed,

and S. Laporte, "Analysis of AIMD-based DSM for EV wireless charging on the move," in *2016 International Conference on Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles & International Transportation Electrification Conference (ESARS-ITEC).* IEEE, nov 2016, pp. 1–8. [Online]. Available: http://ieeexplore.ieee.org/document/7841403/

[56] T. V. Theodoropoulos, I. G. Damousis, and A. J. Amditis, "Demand-Side Management ICT for Dynamic Wireless EV Charging," *IEEE Transactions on Industrial Electronics*, vol. 63, no. 10, pp. 6623–6630, oct 2016. [Online]. Available: http://ieeexplore.ieee.org/document/7471472/

[57] J. W. Heron, H. Sun, O. Alizadeh-Mousavi, and A. Crossland, "Key performance-cost tradeoffs in smart electric vehicle charging with distributed generation," *IET Smart Grid*, pp. 1–21, 2021.

[58] X. Mou, Y. Zhang, J. Jiang, and H. Sun, "Achieving low carbon emission for dynamically charging electric vehicles through renewable energy integration," *IEEE Access*, vol. 7, pp. 118 876–118 888, 2019.

[59] Y. Zhang, H. H.-C. Iu, T. Fernando, F. Yao, and K. Emami, "Cooperative dispatch of bess and wind power generation considering carbon emission limitation in australia," *IEEE Transactions on Industrial Informatics*, vol. 11, no. 6, pp. 1313–1323, 2015.

[60] M. Vasirani, R. Kota, R. L. G. Cavalcante, S. Ossowski, and N. R. Jennings, "An agent-based approach to virtual power plants of wind power generators and electric vehicles," *IEEE Transactions on Smart Grid*, vol. 4, no. 3, pp. 1314–1322, Sep. 2013.

[61] R. Carvalho, L. Buzna, R. Gibbens, and F. Kelly, "Critical behaviour in charging of electric vehicles," *New Journal of Physics*, vol. 17, no. 9, pp. 1–11, 2015.

[62] W. Wei, F. Liu, and S. Mei, "Charging strategies of ev aggregator under renewable generation and congestion: A normalized nash equilibrium approach," *IEEE Transactions on Smart Grid*, vol. 7, no. 3, pp. 1630–1641, 2016.

[63] E. Ucer, M. C. Kisacikoglu, M. Yuksel, and A. C. Gurbuz, "An internet-inspired proportional fair ev charging control method," *IEEE Systems Journal*, vol. 13, no. 4, pp. 4292–4302, 2019.

[64] Y. Cui, Z. Hu, and H. Luo, "Optimal day-ahead charging and frequency reserve scheduling of electric vehicles considering the regulation signal uncertainty," *IEEE Transactions on Industry Applications*, vol. 56, no. 5, pp. 5824–5835, 2020.

[65] W.-Y. Chiu, H. Sun, and H. Vincent Poor, "A multiobjective approach to multimicrogrid system design," *IEEE Transactions on Smart Grid*, vol. 6, no. 5, pp. 2263–2272, 2015.

[66] S. Salinas, M. Li, and P. Li, "Multi-objective optimal energy consumption scheduling in smart grids," *IEEE Transactions on Smart Grid*, vol. 4, no. 1, pp. 341–348, 2013.

[67] A. Asrari, S. Lotfifard, and M. S. Payam, "Pareto dominance-based multiobjective optimization method for distribution network reconfiguration," *IEEE Transactions on Smart Grid*, vol. 7, no. 3, pp. 1401–1410, 2016.

[68] Ziming Zhu, S. Lambotharan, Woon Hau Chin, and Zhong Fan, "Overview of demand management in smart grid and enabling wireless communication technologies," *IEEE Wireless Communications*, vol. 19, no. 3, pp. 48–56, jun 2012. [Online]. Available: http://ieeexplore.ieee.org/document/6231159/

[69] P. T. Baboli, M. P. Moghaddam, and M. Eghbal, "Present status and future trends in enabling demand response programs," in *2011 IEEE Power and Energy Society General Meeting*. IEEE, jul 2011, pp. 1–6. [Online]. Available: http://ieeexplore.ieee.org/document/6039608/

[70] "V2G: The journey to commercialisation," Delta Energy & Environment, August, 2018. Accessed: June 20, 2020. [Online]. Available: https://www.delta-ee.com/downloads/1823-v2g-the-journey-to-commercialisation.html

[71] "The match has been made – EVs are ready to support the electricity grid." NUVVE. Accessed: June 20, 2020. [Online]. Available: https://parker-project.com/https://nuvve.com/2019/01/15/the-match-has-been-made-evs-are-ready-to-support-the-electricity-grid/

[72] "Electric Nation Vehicle to Grid project announces Flexitricity as first energy partner." Flexitricity. Accessed: April 11, 2021. [Online]. Available: https://www.flexitricity.com/resources/press-release/electric-nation-vehicle-grid-project-announces-flexitricity-first-energy-partner/

[73] L. Cheng and T. Yu, "Game-theoretic approaches applied to transactions in the open and ever-growing electricity markets from the perspective of power demand response: An overview," *IEEE Access*, vol. 7, pp. 25 727–25 762, 2019.

[74] G. R. Chandra Mouli, M. Kefayati, R. Baldick, and P. Bauer, "Integrated pv charging of ev fleet based on energy prices, v2g, and offer of reserves," *IEEE Transactions on Smart Grid*, vol. 10, no. 2, pp. 1313–1325, 2019.

[75] D. Liu, W. Wang, L. Wang, H. Jia, and M. Shi, "Dynamic pricing strategy of electric vehicle aggregators based on ddpg reinforcement learning algorithm," *IEEE Access*, vol. 9, pp. 21 556–21 566, 2021.

[76] T. M. Aljohani, A. F. Ebrahim, and O. A. Mohammed, "Dynamic real-time pricing mechanism for electric vehicles charging considering optimal microgrids energy management system," *IEEE Transactions on Industry Applications*, vol. 57, no. 5, pp. 5372–5381, 2021.

[77] X. Chen and K.-C. Leung, "Non-cooperative and cooperative optimization of scheduling with vehicle-to-grid regulation services," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 1, pp. 114–130, 2020.

[78] A. Brooks, E. Lu, D. Reicher, C. Spirakis, and B. Weihl, “Demand dispatch,” *IEEE Power and Energy Magazine*, vol. 8, no. 3, pp. 20–29, May 2010.

[79] E. Sortomme and M. A. El-Sharkawi, “Optimal scheduling of vehicle-to-grid energy and ancillary services,” *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 351–359, March 2012.

[80] M. de Weerdt, G. Morales-Espana, and K. van der Linden, “Optimal Non-Zero Price Bids for EVs in Energy and Reserves Markets Using Stochastic Optimization,” in *2018 15th International Conference on the European Energy Market (EEM)*. IEEE, jun 2018, pp. 1–5. [Online]. Available: https://ieeexplore.ieee.org/document/8470023/

[81] S. I. Vagropoulos and A. G. Bakirtzis, “Optimal Bidding Strategy for Electric Vehicle Aggregators in Electricity Markets,” *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 4031–4041, nov 2013. [Online]. Available: http://ieeexplore.ieee.org/document/6582687/

[82] V. Gupta, S. R. Konda, R. Kumar, and B. K. Panigrahi, “Multiaggregator Collaborative Electric Vehicle Charge Scheduling Under Variable Energy Purchase and EV Cancelation Events,” *IEEE Transactions on Industrial Informatics*, vol. 14, no. 7, pp. 2894–2902, jul 2018. [Online]. Available: https://ieeexplore.ieee.org/document/8125177/

[83] H. Wu, M. Shahidehpour, A. Alabdulwahab, and A. Abusorrah, “A Game Theoretic Approach to Risk-Based Optimal Bidding Strategies for Electric Vehicle Aggregators in Electricity Markets With Variable Wind Energy Resources,” *IEEE Transactions on Sustainable Energy*, vol. 7, no. 1, pp. 374–385, jan 2016. [Online]. Available: http://ieeexplore.ieee.org/document/7349233/

[84] M. G. Vayá and G. Andersson, “Self scheduling of plug-in electric vehicle

aggregator to provide balancing services for wind power," *IEEE Transactions on Sustainable Energy*, vol. 7, no. 2, pp. 886–899, April 2016.

[85] Y. Vardanyan, F. Banis, S. A. Pourmousavi, and H. Madsen, "Optimal coordinated bidding of a profit-maximizing ev aggregator under uncertainty," in *2018 IEEE International Energy Conference (ENERGYCON)*, June 2018, pp. 1–6.

[86] T. Lu, W. Lee, Q. Ai, and S. Lu, "A priority decision making based bidding strategy for interactive aggregators," *IEEE Transactions on Industry Applications*, vol. 54, no. 6, pp. 5569–5578, Nov 2018.

[87] J. Lin, K.-C. Leung, and V. O. K. Li, "Optimal Scheduling With Vehicle-to-Grid Regulation Service," *IEEE Internet of Things Journal*, vol. 1, no. 6, pp. 556–569, dec 2014. [Online]. Available: http://ieeexplore.ieee.org/document/6918361/

[88] Y. Cao, T. Wang, O. Kaiwartya, G. Min, N. Ahmad, and A. H. Abdullah, "An ev charging management system concerning drivers' trip duration and mobility uncertainty," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 48, no. 4, pp. 596–607, April 2018.

[89] S. I. Vagropoulos and A. G. Bakirtzis, "Optimal Bidding Strategy for Electric Vehicle Aggregators in Electricity Markets," *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 4031–4041, nov 2013. [Online]. Available: http://ieeexplore.ieee.org/document/6582687/

[90] S. I. Vagropoulos, D. K. Kyriazidis, and A. G. Bakirtzis, "Real-time charging management framework for electric vehicle aggregators in a market environment," *IEEE Transactions on Smart Grid*, vol. 7, no. 2, pp. 948–957, March 2016.

[91] E. Sortomme and M. A. El-Sharkawi, "Optimal scheduling of vehicle-to-grid

energy and ancillary services," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 351–359, 2012.

[92] H. Nakano, I. Nawata, S. Inagaki, A. Kawashima, T. Suzuki, A. Ito, and W. Kempton, "Aggregation of v2h systems to participate in regulation market," *IEEE Transactions on Automation Science and Engineering*, vol. 18, no. 2, pp. 668–680, 2021.

[93] N. Mizuta, Y. Susuki, Y. Ota, and A. Ishigame, "Synthesis of spatial charging/discharging patterns of in-vehicle batteries for provision of ancillary service and mitigation of voltage impact," *IEEE Systems Journal*, vol. 13, no. 3, pp. 3443–3453, 2019.

[94] S. Cai and R. Matsuhashi, "Model predictive control for ev aggregators participating in system frequency regulation market," *IEEE Access*, vol. 9, pp. 80 763–80 771, 2021.

[95] H. Nezamabadi and M. Setayesh Nazar, "Arbitrage strategy of virtual power plants in energy, spinning reserve and reactive power markets," *IET Generation, Transmission & Distribution*, vol. 10, no. 3, pp. 750–763, feb 2016. [Online]. Available: http://digital-library.theiet.org/content/journals/10.1049/iet-gtd.2015.0402

[96] N. Pourghaderi, M. Fotuhi-Firuzabad, M. Kabirifar, and M. Moeini-Aghtaie, "Energy scheduling of a technical virtual power plant in presence of electric vehicles," in *2017 Iranian Conference on Electrical Engineering (ICEE)*. IEEE, may 2017, pp. 1193–1198. [Online]. Available: http://ieeexplore.ieee.org/document/7985223/

[97] Z. Liu, W. Zheng, F. Qi, L. Wang, B. Zou, F. Wen, and Y. Xue, "Optimal dispatch of a virtual power plant considering demand response and carbon trading," *Energies*, vol. 11, no. 6, 2018. [Online]. Available: http://www.mdpi.com/1996-1073/11/6/1488

[98] W. Hua, D. Li, H. Sun, and P. Matthews, "Unit commitment in achieving low carbon smart grid environment with virtual power plant," in *2017 International Smart Cities Conference (ISC2)*. IEEE, sep 2017, pp. 1–6. [Online]. Available: http://ieeexplore.ieee.org/document/8090810/

[99] M. G. M. Abdolrasol, M. A. Hannan, A. Mohamed, U. A. U. Amiruldin, I. B. Z. Abidin, and M. N. Uddin, "An optimal scheduling controller for virtual power plant and microgrid integration using the binary backtracking search algorithm," *IEEE Transactions on Industry Applications*, vol. 54, no. 3, pp. 2834–2844, May 2018.

[100] Q. Zhao, Y. Shen, and M. Li, "Control and Bidding Strategy for Virtual Power Plants With Renewable Generation and Inelastic Demand in Electricity Markets," *IEEE Transactions on Sustainable Energy*, vol. 7, no. 2, p. vpp7, apr 2016. [Online]. Available: http://ieeexplore.ieee.org/document/7366600/

[101] G. Chalkiadakis, V. Robu, R. Kota, A. Rogers, and N. R. Jennings, "Cooperatives of distributed energy resources for efficient virtual power plants," pp. 787–794, 2011. [Online]. Available: http://dl.acm.org/citation.cfm?id=2031678.2031730

[102] E. Dall'Anese, S. S. Guggilam, A. Simonetto, Y. C. Chen, and S. V. Dhople, "Optimal regulation of virtual power plants," *IEEE Transactions on Power Systems*, vol. 33, no. 2, pp. 1868–1881, March 2018.

[103] E. Mashhour and S. M. Moghaddas-Tafreshi, "A review on operation of micro grids and virtual power plants in the power markets," in *2009 2nd International Conference on Adaptive Science Technology (ICAST)*, Jan 2009, pp. 273–277.

[104] S. Ghavidel, L. Li, J. Aghaei, T. Yu, and J. Zhu, "A review on the virtual power plant: Components and operation systems," in *2016 IEEE International Conference on Power System Technology (POWERCON)*, Sep. 2016, pp. 1–6.

[105] H. Saboori, M. Mohammadi, and R. Taghe, "Virtual power plant (vpp), definition, concept, components and types," in *2011 Asia-Pacific Power and Energy Engineering Conference*, March 2011, pp. 1–4.

[106] C. Binding, D. Gantenbein, B. Jansen, O. Sundström, P. B. Andersen, F. Marra, B. Poulsen, and C. Træholt, "Electric vehicle fleet integration in the danish edison project - a virtual power plant on the island of bornholm," in *IEEE PES General Meeting*, July 2010, pp. 1–8.

[107] D. Thomas, M. Iain, and G. Dale, "Virtual power plants leveraging energy flexibility in regional markets," *CIRED - Open Access Proceedings Journal*, vol. 2017, no. 1, pp. 2939–2943, oct 2017. [Online]. Available: http://digital-library.theiet.org/content/journals/10.1049/oap-cired.2017.0867

[108] S. Pazouki, A. Mohsenzadeh, S. Ardalan, and M.-R. Haghifam, "Simultaneous Planning of PEV Charging Stations and DGs Considering Financial, Technical,and Environmental Effects," *Canadian Journal of Electrical and Computer Engineering*, vol. 38, no. 3, pp. 238–245, 2015. [Online]. Available: http://ieeexplore.ieee.org/document/7270415/

[109] S. Shojaabadi, S. Abapour, M. Abapour, and A. Nahavandi, "Optimal planning of plug-in hybrid electric vehicle charging station in distribution network considering demand response programs and uncertainties," *IET Generation, Transmission & Distribution*, vol. 10, no. 13, pp. 3330–3340, oct 2016. [Online]. Available: http://digital-library.theiet.org/content/journals/10.1049/iet-gtd.2016.0312

[110] H. Simorgh, H. Doagou-Mojarrad, H. Razmi, and G. B. Gharehpetian, "Cost-based optimal siting and sizing of electric vehicle charging stations considering demand response programmes," *IET Generation, Transmission & Distribution*, vol. 12, no. 8, pp. 1712–1720, apr 2018. [Online]. Available: http://digital-library.theiet.org/content/journals/10.1049/iet-gtd.2017.1663

[111] H. Zhang, S. J. Moura, Z. Hu, W. Qi, and Y. Song, "Joint PEV Charging Network and Distributed PV Generation Planning Based on Accelerated Generalized Benders Decomposition," *IEEE Transactions on Transportation Electrification*, vol. 4, no. 3, pp. 789–803, sep 2018. [Online]. Available: https://ieeexplore.ieee.org/document/8384307/

[112] J. Zhao, Z. Xu, J. Wang, C. Wang, and J. Li, "Robust Distributed Generation Investment Accommodating Electric Vehicle Charging in a Distribution Network," *IEEE Transactions on Power Systems*, vol. 33, no. 5, pp. 4654–4666, sep 2018. [Online]. Available: https://ieeexplore.ieee.org/document/8267098/

[113] H. H. Eldeeb, A. O. Hariri, C. R. Lashway, and O. A. Mohammed, "Optimal sizing of inverters and energy storage for power oscillation limiting in grid connected large scale Electric Vehicle park with renewable energy," in *2017 IEEE Transportation Electrification Conference and Expo (ITEC)*. IEEE, jun 2017, pp. 288–293. [Online]. Available: http://ieeexplore.ieee.org/document/7993286/

[114] O. Erdinc, A. Tascikaraoglu, N. G. Paterakis, I. Dursun, M. C. Sinim, and J. P. S. Catalao, "Comprehensive Optimization Model for Sizing and Siting of DG Units, EV Charging Stations, and Energy Storage Systems," *IEEE Transactions on Smart Grid*, vol. 9, no. 4, pp. 3871–3882, jul 2018. [Online]. Available: https://ieeexplore.ieee.org/document/8119897/

[115] J. Ugirumurera and Z. J. Haas, "Optimal Capacity Sizing for Completely Green Charging Systems for Electric Vehicles," *IEEE Transactions on Transportation Electrification*, vol. 3, no. 3, pp. 565–577, sep 2017. [Online]. Available: http://ieeexplore.ieee.org/document/7942095/

[116] R. Xie, W. Wei, M. E. Khodayar, J. Wang, and S. Mei, "Planning Fully Renewable Powered Charging Stations on Highways: A Data-Driven Robust Optimization Approach," *IEEE Transactions on Transportation*

*Electrification*, vol. 4, no. 3, pp. 817–830, sep 2018. [Online]. Available: https://ieeexplore.ieee.org/document/8390898/

[117] "Design of an electric vehicle fast-charging station with integration of renewable energy and storage systems," *International Journal of Electrical Power & Energy Systems*, vol. 105, pp. 46–58, feb 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0142061518308019

[118] N. Banol Arias, A. Tabares, J. F. Franco, M. Lavorato, and R. Romero, "Robust Joint Expansion Planning of Electrical Distribution Systems and EV Charging Stations," *IEEE Transactions on Sustainable Energy*, vol. 9, no. 2, pp. 884–894, apr 2018. [Online]. Available: http://ieeexplore.ieee.org/document/8070965/

[119] S. Pazouki, A. Mohsenzadeh, M.-R. Haghifam, and S. Ardalan, "Simultaneous Allocation of Charging Stations and Capacitors in Distribution Networks Improving Voltage and Power Loss," *Canadian Journal of Electrical and Computer Engineering*, vol. 38, no. 2, pp. 100–105, 2015. [Online]. Available: http://ieeexplore.ieee.org/document/7097124/

[120] Y. Xiong, J. Gan, B. An, C. Miao, and A. L. C. Bazzan, "Optimal Electric Vehicle Fast Charging Station Placement Based on Game Theoretical Framework," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 8, pp. 2493–2504, aug 2018. [Online]. Available: https://ieeexplore.ieee.org/document/8064175/

[121] A. Y. S. Lam, Yiu-Wing Leung, and Xiaowen Chu, "Electric Vehicle Charging Station Placement: Formulation, Complexity, and Solutions," *IEEE Transactions on Smart Grid*, vol. 5, no. 6, pp. 2846–2856, nov 2014. [Online]. Available: http://ieeexplore.ieee.org/document/6879337/

[122] J. Zhao, Z. Xu, J. Wang, C. Wang, and J. Li, "Robust distributed generation investment accommodating electric vehicle charging in a distribution network," *IEEE Transactions on Power Systems*, vol. 33, no. 5, pp. 4654–4666, Sep. 2018.

[123] M. Roozbehani, M. A. Dahleh, and S. K. Mitter, "Volatility of Power Grids Under Real-Time Pricing," *IEEE Transactions on Power Systems*, vol. 27, no. 4, pp. 1926–1940, nov 2012. [Online]. Available: http://ieeexplore.ieee.org/document/6197252/

[124] ——, "Volatility of Power Grids Under Real-Time Pricing," *IEEE Transactions on Power Systems*, vol. 27, no. 4, pp. 1926–1940, nov 2012. [Online]. Available: http://ieeexplore.ieee.org/document/6197252/

[125] J. Wang, M. A. Biviji, and W. M. Wang, "Lessons learned from smart grid enabled pricing programs," in *2011 IEEE Power and Energy Conference at Illinois*. IEEE, feb 2011, pp. 1–7. [Online]. Available: http://ieeexplore.ieee.org/document/5740488/

[126] "DEPsys - Rethink energy." [Online]. Available: https://www.depsys.ch/

[127] "Future Energy Scenarios," National Grid, Gallows Hill, Warwick, UK, July 2018. Accessed: June 10, 2020. [Online]. Available: https://www.nationalgrideso.com/sites/eso/files/documents/fes-interactive-version-final.pdf

[128] L. Liu, F. Kong, X. Liu, Y. Peng, and Q. Wang, "A review on electric vehicles interacting with renewable energy in smart grid," *Renewable and Sustainable Energy Reviews*, vol. 51, pp. 648–661, 2015.

[129] "Future of balancing services." National Grid ESO. Accessed: April 8, 2021. [Online]. Available: https://www.nationalgrideso.com/research-publications/future-balancing-services

[130] J. Matevosyan, S. H. Huang, P. Du, N. Mago, and R. Guiyab, "Operational security: The case of texas," *IEEE Power and Energy Magazine*, vol. 19, no. 2, pp. 18–27, 2021.

[131] "Ancillary services report 2017," Energy UK, April, 2017. Accessed: June 15, 2020. [Online]. Available: https://www.energy-uk.org.uk/publication.html?task=file.download&id=6138

[132] A. F. Raab, M. Ferdowsi, E. Karfopoulos, I. G. Unda, S. Skarvelis-Kazakos, P. Papadopoulos, E. Abbasi, L. M. Cipcigan, N. Jenkins, N. Hatziargyriou, and K. Strunz, "Virtual power plant control concepts with electric vehicles," in *Proc. 16th International Conference on Intelligent System Applications to Power Systems*, 2011, pp. 1–6, Hersonissos, Greece.

[133] W. Hua, D. Li, H. Sun, and P. Matthews, "Stackelberg game-theoretic model for low carbon energy market scheduling," *IET Smart Grid*, vol. 3, no. 1, pp. 31–41, 2020.

[134] W. Nicholson and C. Snyder, "Demand Curves," in *Intermediate microeconomics and its application*, MA, USA: CENGAGE Learning, 2014, pp. 79-120.

[135] J. Gruber, "14.01SC Principles of Microeconomics." [Online]. Available: https://ocw.mit.edu/courses/economics/14-01sc-principles-of-microeconomics-fall-2011/#

[136] "Powered up: Esther Dudek talks about working on the world's largest domestic electric vehicle smart charging trial." EA Technology. Accessed: November 28, 2019. [Online]. Available: https://www.eatechnology.com/blog/2019/11/11/powered-up/

[137] "Trading." National Grid ESO. Accessed: April 10, 2021. [Online]. Available: https://www.nationalgrideso.com/industry-information/balancing-services/trading

[138] C. Develder, N. Sadeghianpourhamami, M. Strobbe, and N. Refa, "Quantifying flexibility in ev charging as dr potential: Analysis of two real-world data sets," in *Proc. IEEE International Conference on Smart Grid Communications (SmartGridComm)*, 2016, pp. 600–605, Sydney, Australia.

[139] "PVWatts Calculator." pvwatts.nrel.gov Accessed: May 15, 2020 . [Online]. Available: https://pvwatts.nrel.gov/index.php

[140] "My Electric Avenue." EA Technology. Accessed: January 10, 2021 . [Online]. Available: https://eatechnology.com/consultancy-insights/my-electric-avenue/

[141] T. Chen, X. P. Zhang, J. Wang, J. Li, C. Wu, M. Hu, and H. Bian, "A review on electric vehicle charging infrastructure development in the uk," *Journal of Modern Power Systems and Clean Energy*, vol. 8, no. 2, pp. 193–205, 2020.

[142] "Mitsubishi Outlander PHEV charging guide." ZAPMAP. Accessed: December 10, 2021 . [Online]. Available: https://www.zap-map.com/charge-points/mitsubishi-outlander-phev-charging-guide/

[143] "Nissan Leaf charging guide." ZAPMAP. Accessed: December 10, 2021 . [Online]. Available: https://www.zap-map.com/charge-points/nissan-leaf-charging-guide/

[144] "BMW 330e charging guide." ZAPMAP. Accessed: December 10, 2021 . [Online]. Available: https://www.zap-map.com/charge-points/bmw-330e-charging-guide/

[145] "Tesla Model 3 charging guide" ZAPMAP. Accessed: December 10, 2021 . [Online]. Available: https://www.zap-map.com/charge-points/tesla-model-3-charging-guide/

[146] "Business models for commercial electric vehicle charging." Pod Point. Accessed: April 1, 2021. [Online]. Available: https://pod-point.com/guides/business/ev-charging-business-models

[147] B. Lane. "Find a charge point near you on Zap-Map." www.zap-map.com Accessed: March 31, 2021. [Online]. Available: https://www.zap-map.com/live/

[148] "YALMIP Download." YALMIP. Accessed: July 12, 2021. [Online]. Available: https://yalmip.github.io/download/

[149] Gurobi Optimization, LLC, "Gurobi optimizer reference manual," 2020. [Online]. Available: http://www.gurobi.com

[150] E. T. Lau, Q. Yang, G. A. Taylor, A. B. Forbes, P. Wright, and V. N. Livina, "Optimization of carbon emissions in smart grids," in *Proc. 49th International Universities Power Engineering Conference (UPEC)*, 2014, pp. 1–4, Cluj–Napoca, Romania.

[151] "Carbon tracker." MyGridGB. Accessed: April 30, 2021 . [Online]. Available: http://www.mygridgb.co.uk/carbon-tracker/

[152] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: Nsga-ii," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, 2002.

[153] P. A. Martinez Castro and A. Arias Montano, "Robust aerodynamic design optimisation of aerofoils for low reynolds number cases," in *Proc. International Conference on Evolutionary and Deterministic Methods for Design, Optimisation and Control with Applications to Industrial and Societal Problems (EUROGEN)*, 2015, pp. 1–7, Glasgow, UK.

[154] G. L. C.A. Coello Coello and D. Van Veldhuizen, "Demand Curves," in *Evolutionary Algorithms for Solving Multi-Objective Problems*, New York, NY: Springer, 2007, pp. 3-18.

[155] I. Giagkiozis and P. J. Fleming, "Pareto Front Estimation for Decision Making," *Evolutionary Computation*, vol. 22, no. 4, pp. 651–678, 2014.

[156] "Project: Western Power Distribution - Electric Nation." EA Technology Accessed: January 30, 2021 . [Online]. Available: https://eatechnology.com/sea/resources/projects/wpd-s-electric-nation-project/

[157] J. Stiasny, T. Zufferey, G. Pareschi, D. Toffanin, G. Hug, and K. Boulouchos, "Sensitivity analysis of electric vehicle impact on low-voltage distribution grids," *Electric Power Systems Research*, vol. 191, p. 106696, 2021.

[158] Y. Zhou, S. Cao, and J. L. Hensen, "An energy paradigm transition framework from negative towards positive district energy sharing networks—battery cycling aging, advanced battery management strategies, flexible vehicles-to-buildings interactions, uncertainty and sensitivity analysis," *Applied Energy*, vol. 288, p. 116606, 2021.

[159] T. Zhu, R. G. Wills, R. Lot, X. Kong, and X. Yan, "Optimal sizing and sensitivity analysis of a battery-supercapacitor energy storage system for electric vehicles," *Energy*, vol. 221, p. 119851, 2021.

[160] F. Ferretti, A. Saltelli, and S. Tarantola, "Trends in sensitivity analysis practice in the last decade," *Science of The Total Environment*, vol. 568, pp. 666–670, 2016.