EFFICIENT OPERATION OF RECHARGING INFRASTRUCTURE FOR THE ACCOMMODATION OF ELECTRIC VEHICLES: A DEMAND DRIVEN APPROACH

Charilaos Latinopoulos

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Centre for Transport Studies
Department of Civil and Environmental Engineering
Imperial College London

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Copyright Declaration

Declaration of Originality

My research has been established in collaboration with my supervisors Professor John Polak and Dr Aruna Sivakumar. Our collaborative research papers have been presented at several conferences and this work has been properly referenced in this thesis. Therefore, I declare that the research presented in this thesis is my own, except where the work of others is referenced.

Charilaos Latinopoulos

October 2015

Abstract

Large deployment and adoption of electric vehicles in the forthcoming years can have significant environmental impact, like mitigation of climate change and reduction of traffic-induced air pollutants. At the same time, it can strain power network operations, demanding effective load management strategies to deal with induced charging demand.

One of the biggest challenges is the complexity that electric vehicle (EV) recharging adds to the power system and the inability of the existing grid to cope with the extra burden. Charging coordination should provide individual EV drivers with their requested energy amount and at the same time, it should optimise the allocation of charging events in order to avoid disruptions at the electricity distribution level. This problem could be solved with the introduction of an intermediate agent, known as the aggregator or the charging service provider (CSP). Considering out-of-home charging infrastructure, an additional role for the CSP would be to maximise revenue for parking operators.

This thesis contributes to the wider literature of electro-mobility and its effects on power networks with the introduction of a choice-based revenue management method. This approach explicitly treats charging demand since it allows the integration of a decentralised control method with a discrete choice model that captures the preferences of EV drivers. The sensitivities to the joint charging/parking attributes that characterise the demand side have been estimated with EV-PLACE, an online administered stated preference survey.

The choice-modelling framework assesses simultaneously out-of-home charging behaviour with scheduling and parking decisions. Also, survey participants are presented with objective probabilities for fluctuations in future prices so that their response to dynamic pricing is investigated. Empirical estimates provide insights into the value that individuals place to the various attributes of the services that are offered by the CSP.

The optimisation of operations for recharging infrastructure is evaluated with SOCSim, a micro-simulation framework that is based on activity patterns of London residents. Sensitivity analyses are performed to examine the structural properties of the model and its benefits compared to an uncontrolled scenario are highlighted. The application proposed in this research is practice-ready and recommendations are given to CSPs for its full-scale implementation.

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List of Acronyms

AC: Alternative Current

ADP: Approximate Dynamic Programming

AER: All Electric Range

AFV: Alternative Fuel Vehicle

A/S: Ancillary Services

ARMA: Auto Regressive Moving Average

ASC: Alternative Specific Constant

AVC: Asymptotic Variance Covariance

AVID: Advanced Vehicle Introduction Decision

AVTA: Advanced Vehicle Testing Activity

BETTA: British Electricity Trading Transmission Arrangement

BEV: Battery Electric Vehicle

BIC: Bayesian Information Criterion

CAN: Control Area Network

CAPI: Computer Aided Personal Interview

CARA: Constant Absolute Risk Aversion

CDLP: Choice-based Deterministic Linear Program

CPM: Charging Point Manager

CRRA: Constant Relative Risk Aversion

CHP: Combined Heat and Power

CISDE: Charging Induced Schedule Delay Early

CISDL: Charging Induced Schedule Delay Late

CNG: Compressed Natural Gas

CNL: Cross-Nested Logit

CSP: Charging Service Provider

DAVN: Displacement Adjusted Virtual Nesting

DC: Direct Current

DCM: Discrete Choice Model

DEU: Discounted Expected Utility

DLP: Deterministic Linear Programming

DNO: Distribution Network Operator

DSM: Demand Side Management

DSO: Distribution System Operator

EC: European Commission

EM: Expectation-Maximization

EMSR: Expected Marginal Seat Revenue

EPRI: Electric Power Research Institute

E-REV: Extended-Range Electric Vehicle

ESP: Energy Service Provider

EUT: Expected Utility Theory

EV: Electric Vehicle

EVM: Electric Vehicle Metering device

EV-PLACE: EV Plug And ChargE

EVSA: Electric Vehicle Suppliers-Aggregators

EVSE: Electric Vehicle Supply Equipment

FCFS: First Come First Served

FPN: Final Physical Notification

GA: Genetic Algorithm

GCSE: General Certificate of Secondary Education

GHG: Greenhouse Gas

GPS: Global Positioning System

GS: Gaming and Simulation

HB: Hierarchical Bayes

HCM: Hybrid Choice Model

HEV: Hybrid Electric Vehicle

HFCV: Hydrogen Fuel Cell Vehicle

HPLC: Hybrid Panel Latent Class

ICE: Internal Combustion Engine

ICLV: Integrated Choice and Latent Variable

ICT: Information and Communication Technology

IEA: International Energy Agency

IEC: International Electrotechnical Commission

IEMS: Intelligent Energy Management System

IID: Independently and Identically Distributed

INL: Idaho National Laboratory

IPF: Iterative Proportional Fitting

IPN: Initial Physical Notification

JARI: Japan Automobile Research Institute

LC: Latent Class

LCGNL: Latent Class Generalised Nested Logit

LCL: Low Carbon London

LIML: Limited Information Maximum Likelihood

LMP: Locational Marginal Pricing

LP: Locational Pricing

LR: Lagrangian Relaxation

LTDS: London Travel Demand Survey

MAS: Multi-Agent System

MD: Mechanism Design

MHLS: Modified Latin Hypercube Sampling

ML: Mixed Logit

MNL: Multinomial Logit

MP: Mathematical Programming

NGC: National Grid Company

NHTS: National Household Travel Survey

NL: Nested Logit

NLP: Non-Locational Pricing

NPS: Net Promoter Score

NTS: National Travel Survey

OD: Origin Destination

OFGEM: Office of Gas and Electricity Markets

OLEV: Office for Low Emission Vehicles

PAT: Preferred Arrival Time

PCP: Personal Contract Purchase

PHEV: Plugged-in Hybrid Electric Vehicle

PiP: Plugged-in-Places

PIREG: Purchase Intention and Range simulation Games

PLC: Panel Latent Class

PMC: Pseudo Monte Carlo

PMM: Profit Maximisation Model

PSO: Particle Swarm Optimisation

PT: Prospect Theory

PV: Photovoltaic Panels

QMC: Quasi random Monte Carlo

RDEU: Rank-Dependent Expected Utility

RCP: Randomised Concave Programming

RLP: Randomised Linear Programming

RLT: Reformulation-Linearization Technique

RM: Revenue Management

RP: Revealed Preferences

RSC: Relabeling, Swapping and Cycling

RUM: Random Utility Model

SBP: System Buy Price

SDCP: Segment-based Deterministic Concave Program

SDE: Schedule Delay Early

SDL: Schedule Delay Late

SOC: State Of Charge

SP: Stated Preferences

SSCNL-BL: Segment Specific Cross Nested Logit with Brand Loyalty

SSP: System Sell Price

TOU: Time Of Use

TSO: Transmission System Operator

TSB: Technology Strategy Board

UBIS: User-Battery Interaction Style

UC: Unit Commitment

UKPN: UK Power Networks

V2G: Vehicle-to-Grid

V2H: Vehicle-to-Home

VAT: Value Added Tax

VMT: Vehicle Miles Travelled

VTAM: Vehicle Technology Assessment Model

WTP: Willingness To Pay

1 INTRODUCTION

1.1 Background

In the UK, domestic transport contributes 20% to total CO_2 emissions, with more than 90% of it coming from road transport, the majority of which is attributed to cars (Figure 1.1). In addition, transport is the main contributor of various localised pollutants produced by tailpipe emissions, like carbon monoxide (CO), nitrogen oxides (NOx) and particulates (PM10) (Meyer, 2009). According to the Fourth Carbon Budget Statement from the Secretary of State for Energy and Climate Change (DECC, 2014a), there is a binding target towards the containment of global warming: the 80% reduction of CO_2 emission by 2050.

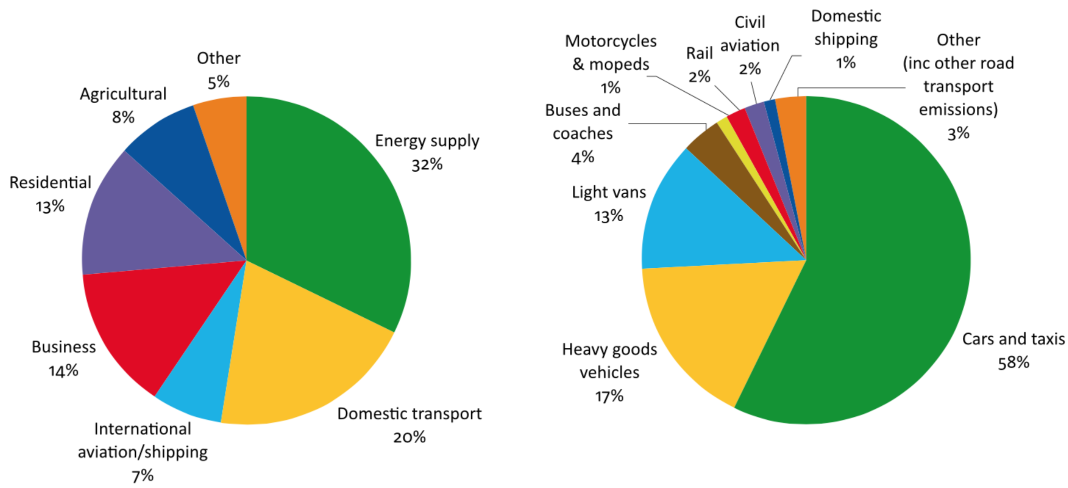


Figure 1.1: Greenhouse gas emissions by sector (left) and domestic transport greenhouse gas emissions (right) Reproduced from (National Atmospheric Emissions Inventory, 2009, figures rounded to the nearest percent)

The electrification of the road transport sector is a key step towards achieving these goals. An electric vehicle (EV) compared to a mid-sized gasoline driven vehicle could achieve a 5%-8% decrease of life-cycle emissions with a battery replacement. If the battery is not replaced, this decrease could reach a percentage of 10%-20% (Ricardo, 2013). According to the IEA technology roadmap for Battery Electric Vehicles (BEVs) and Plugged-in Hybrid Electric Vehicles (PHEVs), there is a potential for 100 million sales of these vehicles by 2050 that will represent more than 50% of the light-duty vehicle fleet (IEA, 2011). In this scenario, the transport contribution is a 30% reduction in CO_2 emissions by 2050 compared to 2005 levels (Figure 1.2).

For the UK, the number of EVs by 2030 is forecasted between 0.5 and 5.8 millions (Arup, 2008). A more recent study (Cambridge Econometrics, 2015) indicates that the annual increase of EV sales in Britain was 300% in 2014 (15,631 new vehicles) and suggests an adoption rate of 10% for BEVs by 2030.

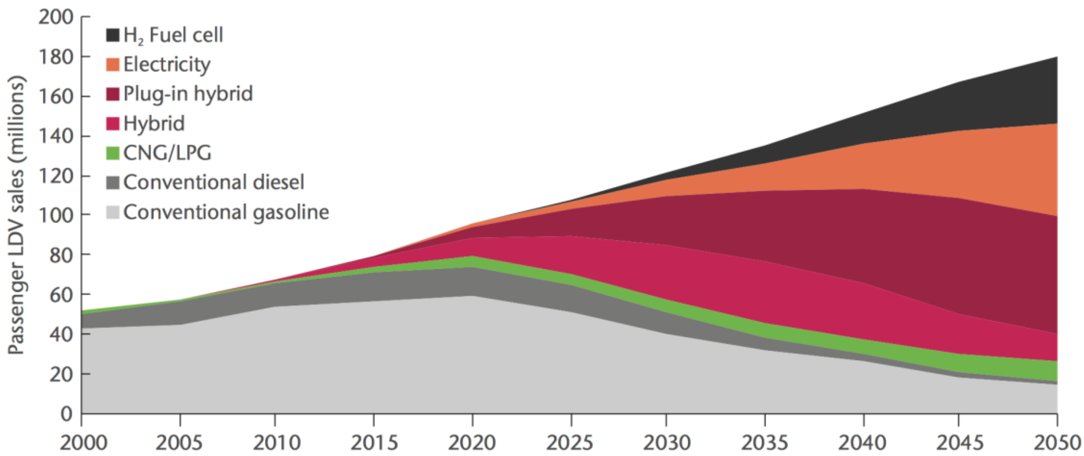


Figure 1.2: Annual passenger LDV sales by technology. Reproduced from (IEA, 2009)

However, in order to reach that point, there is a need to establish strong foundations during the next decade for many aspects of electro-mobility (vehicles, infrastructure, stakeholders, consumers, etc.) and also to develop new partnerships and cooperation channels at the international level. Such an ambition needs to be supported with pilot city projects, transparency, sharing of information and commitment of the private sector. With this framework, the most crucial issue is to stimulate people towards electric mobility and this is why existing policies promote preferential treatment measures, like exemption from congestion charge, vehicle-related taxes (CO_2-based) and governmental grants for the initial purchase of an EV.

Mobility electrification can contribute to the decarbonisation of the transport sector, but at the same time, it may introduce an additional burden to the power grid, especially at a distributional level. The net benefits associated with the use of EVs, depend among others on the spatial and temporal distribution of demand. Therefore, a smart management system is required to utilise current energy and transportation infrastructure efficiently in order to jointly control EV charging demand and residential power sources.

In London two-thirds of the households do not have access to off-street parking (Figure 1.3) (Mayor of London, 2009). The investment in public charging infrastructure is vital in order to encourage the early adoption of EVs and tackle the psychological barriers associated with the reduced driving range that the vehicle's battery allows, known as "range anxiety". However, coordination of EV clusters is a challenging task for public or private parking operators and for all types of facilities that provide parking places (e.g. park and ride stations, shopping malls etc.). Lack of familiarity with the new technology can complicate the management of charging infrastructure by parking operators, resulting in the emergence of intermediate agents, the Charging Service Providers (CSPs). A CSP (or an aggregator agent) functions as a bridge between power market players and individual vehicles. Nevertheless, out-of-home charging would require from this commercial middleman to play an additional role, this of revenue optimiser for the collaborating parking facilities.

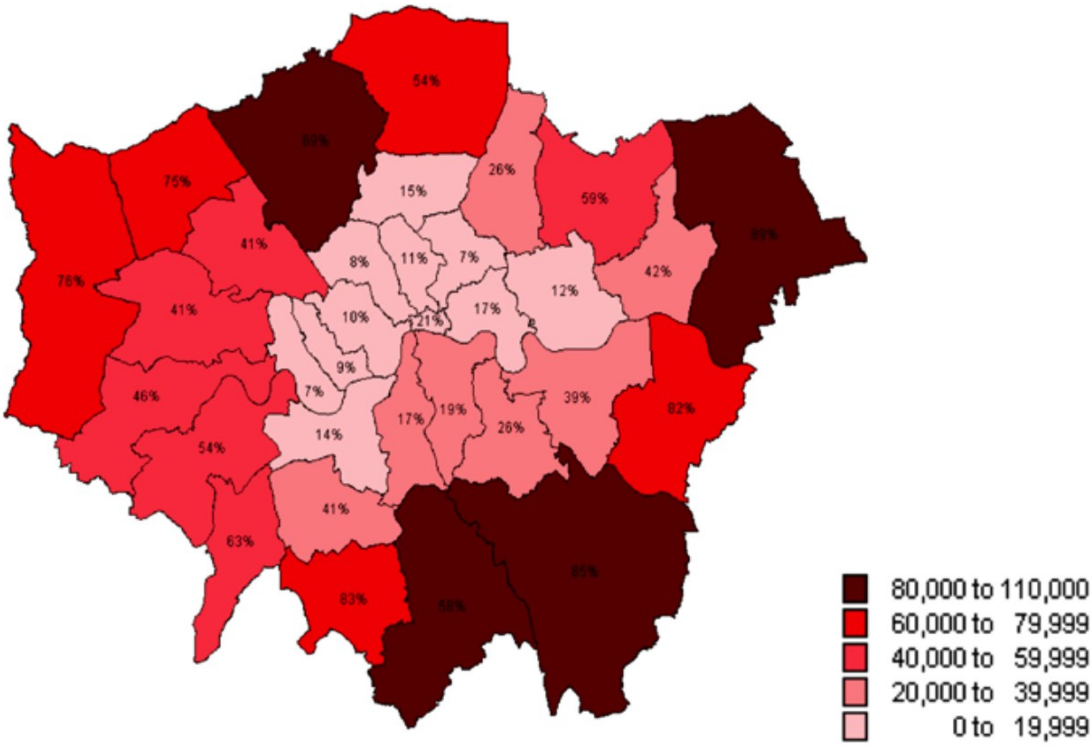


Figure 1.3: Households with off-street parking accessibility in London – The numbers on the map indicate the percentages for each borough. Reproduced from (Mayor of London, 2009)

In this evolving market of EV charging services, it is essential to identify the heterogeneity among the different types of customers, and how this market segmentation would affect the delivery and management process. Demand-management decisions aiming at increasing revenues can be approached through the theory of Revenue Management (RM). RM applications have been successfully applied in various service industries (e.g. air tickets, hotel rooms, parking facilities etc.), either in the form of capacity allocation or in the form of dynamic pricing. The complexity of extending these traditional approaches to accommodate charging infrastructure management lies in the characterisation of the product itself and the multidimensional nature of the recharging capacity.

Any management process heavily relies on the proper understanding and representation of demand. Previous research has either ignored EV drivers' behaviour and their response to charging incentives, or introduced extreme assumptions for charging scenarios. An increasing number of trials and demonstration projects have analysed movements and recharging profiles of EV users by combining in-vehicle and charging post loggers. However, the limited scale and variability in these trials is not sufficient to explain charging behaviour under different recharging rates, spatial attributes and most importantly, dynamic pricing scenarios. On the other hand, the majority of stated preference instruments in this field focus on the willingness to buy an electric vehicle rather than on aspects, such as charging behaviour, of their everyday use.

1.2 Aims and Objectives

Building on the background of section 1.1 the aim of this doctoral research is to develop an integrated parking and charging facility management solution for parking operators and CSPs. This requires an innovative platform, where traffic and power networks are merged without compromises for the robust operation of either of them. It also entails the proper understanding of electric vehicle users' travel and charging behaviour, since the distribution of demand is the strongest element of uncertainty in the management process.

The specific objectives of the thesis can be summarised as follows:

- To develop a stated preference methodology to characterise the joint preferences for parking and charging associated with out-of-home activities.
- To introduce the concept of reservation in advance that would enhance the prediction capabilities for several stakeholders in the hierarchy of coordination and control, from parking operators to Distribution Network Operators (DNOs).
- To develop techniques for revenue maximisation, varying from capacity allocation among the charging facilities to the dynamic pricing of charging services.
- To identify segments of the market and latent characteristics that could affect the EV drivers' willingness to pay.
- To quantify the various levels of uncertainty ("range anxiety", price volatility etc.) for the drivers and explore the existence of forward-looking behaviours.

- To understand the dynamic interaction of supply and demand (through revenue management with strategic customers) and suggest methods for the estimation of spatiotemporal price equilibriums, indicating the associated operational and policy implications.

1.3 Outline of the thesis

The thesis consists of seven chapters including this one. A brief summary of the contents of the following chapters is given below.

- **Chapter 2** reviews the state of the art in modelling the **demand** for electric vehicles. The characteristics of EV drivers are highlighted and the interrelationships between charging choices and travel choices are discussed. Then the latest developments in charging choice modelling are presented. This chapter also introduces Vehicle-to-Grid technology and how people perceive it. Finally, different data collection methods for EVs are demonstrated along with methods to enrich them.
- **Chapter 3** presents the survey tool that has been administered to collect data for out-of-home EV recharging. The sampling strategy for both piloting and the final deployment are discussed and the model specifications that have defined the attributes and the design levels of the choice experiments are demonstrated. The experimental design is explained and some sample demographics are presented along with a preliminary analysis of driving and charging patterns.
- **Chapter 4** presents the discrete choice-modelling framework that is developed to explain charging behaviour. A latent class model is estimated to identify heterogeneous segments and unobservable behavioural aspects like pre-planning or range anxiety. Moreover, response to the dynamic pricing of electricity for EV recharging is modelled within the context of Expected Utility Theory (EUT) and non-Expected Utility Theory (non-EUT). As it can be seen in Figure 1.4, this chapter along with the previous two chapters highlight the significance of demand for charging coordination and suggest ways to capture the preferences of EV drivers.
- **Chapter 5** is the second review chapter (Chapter 2 being the first one), and this time, the focus is on the **supply** side. The potential complications of EV recharging for power networks are discussed and existing EV fleet management techniques are presented. There is also an introduction to the concepts of smart grid and smart charging as well as to the importance of communication technologies and real-time

metering. The added value of the suggested revenue management approach is emphasised. For this reason, a detailed literature review on revenue management methods and their application in the service industry is also presented.

- **Chapter 6** first sets the conceptual framework of the revenue management problem for the charging service provider. The adjustments and modifications of conventional revenue management methods to accommodate the charging infrastructure problem are discussed. Innovative additions like the multidimensional representation of capacity or the possibility to include Vehicle-To-Grid (V2G) technologies are also presented. Next, a sequential approach with two optimisation steps is developed: a genetic-algorithm-based price optimisation and then a choice-based capacity allocation heuristic with the optimised prices as input. For both algorithms demand is modelled explicitly with the use of the estimated parameters in Chapter 4, as it is illustrated in Figure 1.4.
- **Chapter 7** summarises the findings of the research and presents the conclusions in detail. Finally, this chapter discusses the overall contribution of this research to the electro-mobility area and potential future extensions of the work.

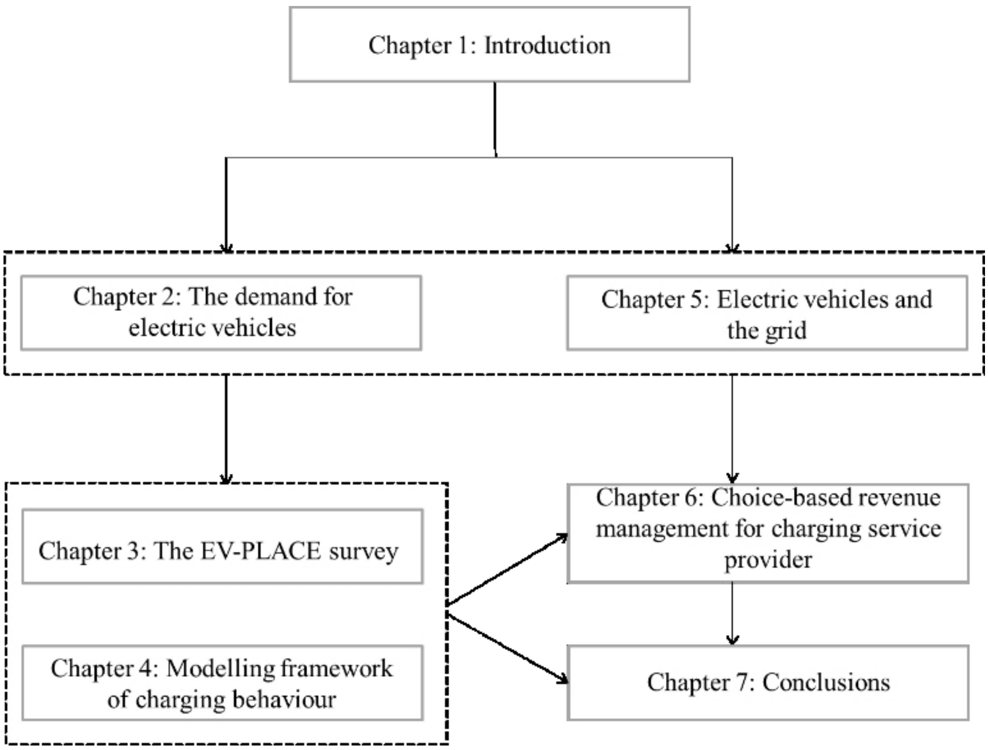


Figure 1.4: Illustration of the outline of the thesis

2 THE DEMAND FOR ELECTRIC VEHICLES

2.1 Overview

The prospect of wide spread of BEVs and PHEVs in the short-term and long-term future is contingent on the ability to foresee drivers' needs and desires as well as to measure their willingness to adopt these vehicles and their willingness to modify their travel behaviour according to the charging requirements. The EV customer aspects that might determine the strategic deployment of electric vehicles can be summarised in the following four categories (IEA, 2011):

- Willingness to pay for BEV/PHEV purchase
- Driving behaviour and required driving range
- Driving style
- Charging behaviour

In this chapter, the existing literature and the state-of-the-art across all these dimensions of the demand for electric vehicles is explored. However, the main objective of the review is to present how EV drivers make recharging choices and what modelling techniques have been applied to capture this behaviour. In this way, it is possible to illustrate the underlying reasons for the selected data collection methods (Chapter 3) and the current deficiencies in treating charging behaviour, which the suggested modelling framework (Chapter 4) attempts to overcome.

Therefore the characteristics of electric vehicles and all the factors that might influence their adoption are discussed, along with some representative studies of the modelling approaches in this area. Then, an overview of the various types of EV drivers is given in order to highlight the importance of segmentation when individuals have different attitudes and perceptions towards mobility, charging constraints and environmental impacts.

The main core of this chapter is the analysis of charging behaviour as it has been observed throughout real world trials or simulation studies. Also, there is a review of methodological approaches and assumptions in modelling charging behaviour. The strengths and weaknesses of the studies are highlighted in a way that indicates the gaps in the literature and justifies the need for a distinctive treatment of demand, similar to the proposed conceptual framework.

Since the overall aim is to investigate the interrelated parking and charging choices of individuals, at this point there is also an extensive discussion about the demand for parking, the attributes that influence parking choice and existing modelling techniques. Moreover, in order to apply demand side management (DSM) methods, like dynamic pricing, it is prerequisite to understand how people would respond in these situations. Risky choices are better explained in Chapter 4 where the demand model is presented. However, here we discuss how people respond to dynamic pricing in a very similar context, i.e. energy consumption at home, and what insights can be gained for the case of electric vehicles. At the end of this subsection, there is a short introduction to Vehicle-to-Grid, mainly from the point of view of the consumer.

Finally, the importance of data collection in electro-mobility research is underlined. There is a detailed description of some prevalent trials around the world and in the UK, and of other indirect methods to elicit drivers' preferences for EV use, like stated preference surveys. In this way, it will be possible in Chapter 3 to demonstrate how the choice experiment of this research differentiates from the previous ones and how it was sequentially evolved to its final version.

It's important to mention that the review of the literature isn't limited to this chapter. The following chapters include parts of literature review as well that apply to their specific purposes:

Chapter 3 reviews the literature on the design of choice experiments and on sampling strategies and survey administration methods that are significant to understand the development of the online survey.

Chapter 4 includes a brief review of activity-travel timing choice models, hybrid choice models and risky choices in order to set the background for the presentation of the demand model specifications

Chapter 5 examines the complications of EVs from the power network perspective. There is an overview of smart charging and optimisation methods for charging operations as well as an analysis of existing business models for EV fleet managers. Finally, there is an extensive review of the revenue management literature and its application in other service industries. This is essential before proceeding with the innovative approach for charging service providers in Chapter 6.

The different bodies of literature that are reviewed across the chapters of this thesis and their interrelationships are illustrated in Figure 2.1.

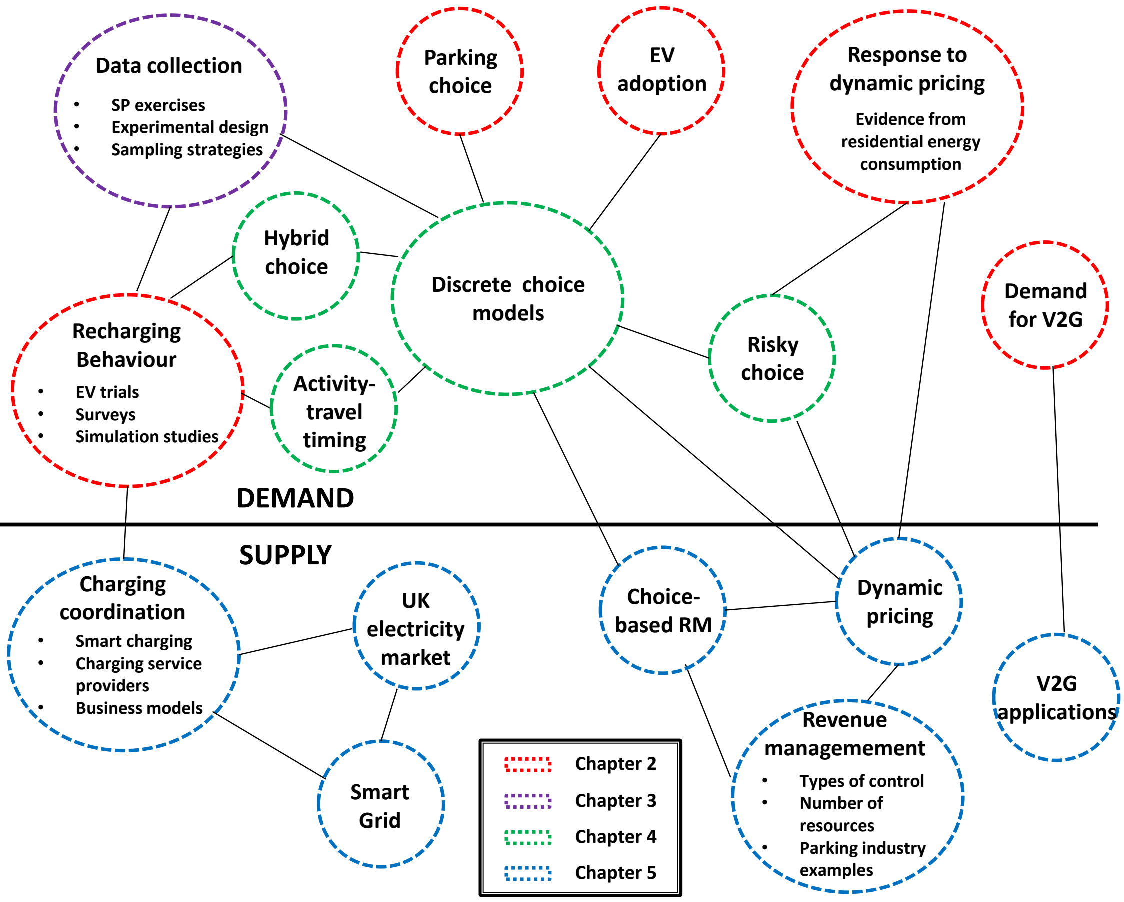


Figure 2.1: Outline of the literature review sections included in the thesis

The structure of the present chapter is the following:

- Section 2.2 presents the various characteristics of electro-mobility, like vehicle types, driver types, charging infrastructure, as well as the main modelling approaches for EV adoption.
- Section 2.3 outlines the different aspects of charging behaviour (frequency, location, range anxiety etc.) and demonstrates the modelling approaches and the numerous assumptions that can be found in the relevant literature. Also, it provides additional information that is useful for the modelling section, like parking choice and response to dynamic pricing. As a result, it highlights the benefits of the joint charging/parking choice framework that is suggested in this thesis and it stresses the need for proper

data collection methods. Finally, the demand for V2G technologies is discussed and some initial beliefs and concepts in this fast developing area are exhibited.

- Section 2.4 gives an overview of the existing EV trials that provide revealed preferences (RP) for charging attributes. At the same time, it shows alternative data collection methods (online surveys, focus groups etc.) that have been employed and their similarities (and dissimilarities) with the stated preference tool presented in the next chapter.
- Section 2.5 summarises and identifies the links of the literature with the following methodological sections.

2.2 The characteristics of electro-mobility and barriers in adoption

2.2.1 Types of electric vehicles

Electric vehicles made their appearance in the mid-19th century. The first practical production electric vehicle was built in London by the English inventor Thomas Parker and it was equipped with high-capacity rechargeable batteries that he designed himself (The Daily Telegraph, 2009). By the end of the 19th century, EVs reached their golden age, with 40% of US automobiles being powered by steam, 38% by electricity and 22% by gasoline. However, a few years later, internal combustion engine (ICE) vehicles surpassed EVs and this could be the result of several factors (e.g. improved road infrastructure, discoveries of large petroleum reserves, low driving range of EVs etc.). Fossil-powered ICE vehicles have dominated the automotive market for decades, until recently when a revival of interest in electric mobility has been observed. This change is mainly driven by environmental pressures in order to reduce transport-related emissions as well as by the continuously rising level of energy prices.

The variety of alternative fuel vehicles (AFVs) in the market today is huge. First of all, there are pure battery electric vehicles (BEVs) that function based on an electric motor for propulsion along with a battery for electricity storage. Their battery is charged from grid and non-grid sources (e.g. photovoltaic panels) as well as from braking energy and their capacity is usually between 25-40kW. Mobility with BEVs is more efficient and less expensive compared to ICE vehicles. They also offer the possibility to reach zero Greenhouse Gas (GHG) and pollutants emissions.

Then there are the hybrid electric vehicles (HEVs) that consist of both an internal combustion engine and an electric motor and the energy stored in their battery (1kW – 2kW capacity) comes either from braking or is generated by the engine. The limited electric driving range of HEVs has encouraged the development of plugged-in hybrid electric vehicles (PHEVs) with higher battery capacity (approximately five times bigger) and the capability to plug-in and draw electricity from the grid. PHEVs can function in *charge depleting mode* when they consume electricity only, in a *blended mode* when they combine electricity and gasoline and in *charge sustaining mode* when they behave like typical HEVs (Delucchi and Lipman, 2010). Several PHEV models can run in an all-electric operation for a few miles, known as the *all-electric range* (AER). These models are often named after their AER. For example, a PHEV20 has a 20-miles AER whereas a PHEV50 has a 50-miles AER.

Finally, Extended-Range Electric Vehicles (E-REVs) are similar to PHEVs, although they have a somewhat larger battery pack and the internal combustion is used as a generator to charge the depleted battery (OLEV, 2011). The list of alternative fuel vehicles also includes hydrogen-fuel-cell vehicles (HFCVs), biofuels and compressed natural gas (CNG), but these are not the focus of this dissertation.

PHEVs are considered as a smooth transition to the next generation of vehicle technologies, with increased energy efficiency and decreased pollution levels (Lemoine et al. 2008). Their attractiveness stems from their combination of long gasoline-based range and their capability to switch into a battery-powered, low-emission driving mode. Furthermore, they allow a significant level of flexibility to their owners to choose if and when they will charge their car.

Their ability to absorb energy from the grid has as a direct effect, the reduction in gasoline consumption. The extent of this reduction cannot be easily estimated because it is highly dependent on the driving style and the design of each vehicle. Nevertheless, Wang (2001) estimated an approximate 60% drop compared to ICEs and 30% drop compared to typical HEVs. This reduction is intrinsically connected with a decrease of tailpipe greenhouse gas emissions. The cost per kWh for PHEVs is 1.3 to 1.5 higher compared to BEVs due to their resistance to depletion and their power-oriented configuration (IEA, 2009).

For the evaluation of the overall environmental impact of PHEVs, apart from the tailpipe emissions, one has to take into consideration the life-cycle emissions (Kurani et al. 2007). Since life-cycle emissions incorporate emissions from upstream electricity generation, they are conditional on the fuel source of the electricity that goes to the PHEVs. Integrating the charging of the vehicles with renewable sources can lead to a substantial reduction in GHG emissions compared to electricity originating from coal-fired power plants. For example, the emission rate, assuming an average grid mix electricity in the UK, is 81.4 g CO_2/km while for CHP (combined heat and power) generation it is 45 g CO_2/km and for renewable sources, it is 0 g CO_2/km (Carroll, 2010).

Several countries around the world are establishing limits to emissions coming from the light-vehicle duty. Some of these countries are Australia, Canada, China, Japan, South Korea and U.S. (Garcia-Villalobos et al., 2014). In Europe, the average CO_2 emissions limit that has been imposed by the European Commission (EC) for new vehicles is 130g CO_2/km in a transition phase between 2012 and 2015, with an intention to be tightened to 95g CO_2/km by 2020 (AEA Group, 2009).

From 2008 to 2014, it has been observed that over 260,000 PHEVs have been sold worldwide (Cobb, 2014). The Chevrolet Volt, the Toyota Prius PHV and the Mitsubishi Outlander P-HEV are considered the best-selling models up to the present. Indicatively, the fuel economy of the Chevrolet Volt is 93 MPG-e (miles per gallon gasoline equivalent when only electricity is used) in all-electric mode, 37mpg in gasoline-only mode and 60mpg for blended operation.

Considering BEVs, Nissan Leaf is the dominant model, counting over 150,000 sales globally until 2014, amongst which 31,000 sales were made in Europe (GreenCarGuide, 2015). Apart from medium-sized vehicles, it is observed that electric sports (Lighting GT) and luxury cars (Tesla Model S) are entering the market as well to improve the environmental-friendly image of the auto manufacturers and to enlarge the potential range of future adopters.

Garcia-Villalobos et al. (2014) in their review study summarise the advantages of EVs compared to ICEs in the following:

- Reduction of oil consumption
- Reduction of GHG emissions
- Improvement of air quality and public health
- Reduction of the cost of travelling
- Capability to exploit local energy sources
- Potential for improvement in power network efficiency and operation

2.2.2 Parameters of EV adoption

Even though there is a coordinated effort to encourage the adoption of these vehicles nowadays, substituting the ICE fleet is not a trivial task and several attempts to reintroduce electro-mobility have failed in the past (Hard and Knie, 2001). Their technological immaturity and their high upfront cost could explain why it is still difficult to promote them. In addition, the long-term dominance of conventional vehicles and their co-evolution with the petroleum industry is endogenously related with the maintenance of low gasoline taxation and the suppression of alternative technologies' development (Struben and Sterman, 2008). Simpson (2006) came to the conclusion that higher gasoline prices and lower manufacturing costs for the batteries could be crucial in order to create a feasible economic scenario for the adoption of EVs in the long term.

In general, there is a trend for private organisations to embrace eco-innovations that would enable them to improve their public image and achieve their sustainability targets. However, the diffusion of such innovation types is rather slow compared to other markets like mobile telecommunications. The determinants of these innovations are: Technology Push, Regulatory Push and Market Pull (Rennings, 2000). Zhang et al. (2011a) suggest that for the alternative fuel vehicles market there are three main players: drivers that try to maximise their utility and minimise their cost, car manufacturers that try to maximise their profits and governmental agencies that try to maximise social benefits. They also elaborate that to achieve a faster diffusion in this area there is a need to study the interrelationship between these players.

Focusing on the market pull domain, some of the main factors that influence the choice for a vehicle purchase are: price, operating cost, performance, driving range, service availability, safety, maintenance requirements and ecological impact. For some of these parameters, like operating cost, the comparison between the various technologies is not straightforward. For example, potential PHEV buyers have to evaluate both fuel consumption and electricity consumption and this requires *a priori* consideration of their driving behaviour, their billing options and their personal preferences. The long-term target should be to make AFVs cost competitive with ICE cars and at the same time to design them in a way that they match or exceed their characteristics.

Furthermore, in order to explore the methods that would facilitate the diffusion of electric vehicles it is important to understand the behavioural dynamics that underlie all sorts of innovation adoption: word of mouth, social exposure and the willingness of consumers to engage with the new technology. One should also take into account that car has always been a source of personal identity and social status (Urry, 2004) and the choice for vehicle adoption is strongly affected by cultural norms and social interactions. Therefore, the willingness to engage with a certain technology is dependent on the exposure of the consumer to the various products, which in turn is a function of marketing and media attention.

Education programmes and demonstration projects are indispensable to increase the level of awareness for the consumer side and to clarify the ambiguities that might hinder the adoption of the new technology. These projects should highlight the advantages of electro-mobility and allow people to test drive different EV technologies. Moreover, continuous research and innovation are required to improve the existing technology.

For example, the evolution of battery technology is crucial for the future of electric mobility, and there are still a lot of issues to overcome like storage capacity, duty (discharge) cycle, reduction in charging time, reduction in cost, durability and life expectancy. Among the existing technologies, lithium-ion has proved to be the best option for storage capacity. Nevertheless, new battery chemistries are currently investigated that could achieve larger ranges and lower costs. A typical battery life is estimated between 10 and 15 years and the exact lifespan is determined by the number of discharges.

Nykvist and Nilson (2015) performed a systematic review of existing estimates for the costs of battery packs and they found an 8% annual decrease among leading BEV manufacturers. They suggested that this decline rate is likely to continue with the construction and successful operation of large-scale production facilities. Combining this observation with the fact that cumulative battery capacity increases more than 100% every year allows optimistic scenarios for the adoption of BEVs in transport and energy policy analysis.

Car sharing systems can also increase the visibility of EVs for drivers and allow those who are hesitant to try them before they proceed with a purchase. Car club companies have presented a significant growth during the last few years, offering an intermediate alternative between costly personal cars and uncomfortable public transport. Some of them[1] include EVs in their fleet and may offer free charging opportunities, facilitating the transition from the early adoption period to a mainstream EV market.

[1] Typical examples are Hertz on Demand in London or Autolib in Paris

One common strategy to overcome the high-cost barrier is to provide incentives in the form of subsidies to electric vehicle drivers or other stakeholders like fleet operators. Tax incentives for HEV drivers were examined in Diamond's (2009) model, and the results showed that their effectiveness depends on the capability of the government to provide them upfront. In the UK, EV owners benefit from a Vehicle Excise Duty while companies that promote plug-in vehicles benefit from Company Car Tax exemptions (OLEV, 2011). Battery subsidies are also necessary to relieve potential buyers from the high-cost premium of electric vehicles. In case battery replacement is required in a shorter term than the life-cycle of the vehicle, innovative business models should be developed to absorb part of the uncertainty from the consumer's side. For example, Renault offers an option, where drivers can buy an EV without purchasing the battery at the same time. In exchange, they can rent the battery paying 45 – 80 Euros per month. Norway, having the highest per capita number of EVs, is considered to be the world leader for EV use and the success in their deployment can be mainly attributed to their key policy orientation towards providing incentives to the users.

The debate for the successful deployment of electric vehicles is typically dominated by the fact that people cannot easily accept the limited driving range and the prolonged duration of a charging event. One of the great advantages that car ownership offers is the spontaneity that drivers enjoy in their trip planning. The phenomenon associated with the limited range and the resulting fear or concern is widely known as "range anxiety" (Tate et al., 2008). According to Nilsson (2011), "Range anxiety emerged as a concept in the late 1990s and captures a drivers' concern of not reaching their destination while travelling in an EV". One of the main questions that are raised is: what is the minimum range that drivers are prepared to settle with, and at what price are they willing to compromise in order to obtain the positive features (environmental benefits, noise reduction etc.)?

2.2.3 Types of electric vehicle drivers

As with many innovations (Rogers, 2003), the diffusion of electric vehicles can be represented as a normal distribution over time. In this distribution, drivers can be classified into five different types: innovators, early adopters, early majority, late majority and laggards. The drivers across these categories have diverse socio-economic and taste characteristics and they differ in their level of propensity to adopt an electric vehicle.

The Advanced Vehicle Introduction Decision (AVID) model, developed by the Argonne National laboratory divides alternative vehicle technology drivers into two groups: early adopters (15%) and majority buyers (85%) (Santini and Vyas, 2005).

The assumption is that the early adopters are, in their majority, environmentally motivated "green" consumers. Kurani et al. (1996) have not verified this assumption. Measuring the willingness to pay for the reduction of pollutants, their results suggest that there is no significant statistical relationship with EV adoption. However, they argue that the eco-friendly image of EVs could increase the number of potential buyers.

Moreover, multi-vehicle households, households with low demand for driving range and households with recharge potential are more likely to be among the early adopters group. Generally, those people are different from the typical consumer and one should be cautious when analysing their behaviour because it's very probable that it is not representative of the mass EV market.

Potential candidates for the early adoption group can be also found in organisations that operate fleets and vehicle pools because the use of vehicles under these conditions is less uncertain and hence more predictable than personally owned cars. Favouring taxation regimes for companies that integrate EVs in their fleets, along with the opportunity that they are given to promote their leadership in sustainability, should encourage them with the initial boost they need to become part of the early adopters.

Mainstream consumers, contrary to early adopters, are not likely to base everyday travel choices on environmental motives. Sampling strategies for field trials are usually biased towards technology enthusiasts or "green" consumers and the attitudinal conclusions cannot be representative of a mainstream future market. Graham-Rowe et al. (2012) are the first in the UK that attempted to reflect mainstream consumers in their sample and to identify the main psychological barriers in purchasing and using an EV.

Market *segmentation* is required in order to classify different types of EV customers and understand the distinctive characteristics of each group. Mohseni and Stevie (2009) have developed a methodology to achieve this segmentation through demographic and attitudinal information, with members of each group having certain homogeneity in their perception of the vehicle and charging characteristics.

Depicting the profile of car buyers, either they belong to the "early adopters" group or to the mainstream market group, can provide valuable information to policymakers and to all industry stakeholders that aim to increase the share of EVs and PHEVs in the light-duty vehicle fleet. Understanding the heterogeneity among these profiles, regarding range anxiety or charging behaviour, could be a decisive factor in overcoming the existing barriers by setting the right prices and addressing the needs of each profile exclusively.

2.2.4 The role of charging infrastructure

In the case of electric vehicles it is crucial to highlight the role of complementary resources, i.e. recharging infrastructure. Drivers will hesitate to proceed with a transition to alternative fuel vehicles without the suitable level of infrastructure availability while on the other hand electro-mobility stakeholders (e.g. energy providers, manufacturers, local authorities etc.) will hesitate to invest in the deployment of these resources without the prospect of an increase in future sales (often referred to as a chicken and egg problem). To increase the environmental impact, it is crucial to support charging infrastructure development in urban areas with “clean” electricity generation but at the same time to ensure adequate electricity supply for the users (IEA, 2011).

The majority of charging activity is anticipated to take place at home due to the convenience that it offers to the drivers. On the other hand, if peak hours are avoided, late-night charging is optimal from the operator’s perspective, as well, because it minimises the cost and the carbon intensity of electricity generation. As a result, governments should facilitate the installation of dedicated domestic charging places. Other out-of-home charging opportunities should be promoted too. For example, the Permitted Development Right in the UK (OLEV, 2011) gives the opportunity to landowners to install charging stations in business parking areas without having to apply for planning permission. In London, based on the Mayor’s London Plan (Mayor of London, 2011), organisations with car parking availability are required to include one charging station for every five parking places. Workplace charging could be also endorsed with discounted electricity prices for infrastructure owners. Finally, public charging posts need to be deployed, not so extensively that they would be underutilised, but in strategic locations to alleviate range anxiety and to facilitate owners without off-street parking availability. Data collected from these public places is vital to understand the charging patterns of the users and assist their commercialization and the formation of new business models.

The Plugged-in Places programme has commenced eight projects across the UK collaborating with the Office for Low Emission Vehicles (OLEV) in order to achieve the installation of 8,500 charging stations in all possible locations described above. Several schemes for users of the infrastructure have emerged from this programme, like ‘Charge Your Car’ in the North East and ‘Source London’ [2] in London, with varying payment methods (membership, prepaid and pay-as-you-go). The standardisation and interoperability of the infrastructure are crucial to enable EV drivers to have access across the different schemes.

Recharging infrastructure functions as an interface between the power grid and the vehicle that can be accessed and managed by the user. The Electric Power Research Institute (EPRI) has defined three levels for charging infrastructure (Morrow et al. 2008):

- **Level 1**: Standard 120V/(12A or 16A) which is the lowest common voltage level that can be encountered in the U.S. and can achieve a maximum of 1.44kW power.
- **Level 2**: Single phase 240V/40A which has been characterised as the “primary” or “preferred” level to charge a BEV and it can be performed with two types of equipment:
    - Conductive equipment with a “butt-type” or “pin and sleeve” connection type, which is otherwise known as the electric vehicle supply equipment (EVSE) that has the advantage of higher efficiency and the potential for bi-directional power flow.
    - Inductive equipment where energy is transferred without metal-to-metal contact and has the advantage of intrinsic safety.
- **Level 3**: Fast charging, three-phase 480V, which is intended to play a role similar to a conventional gasoline fuelling station.

The International Electrotechnical Commission (IEC) has presented a different classification (EVUE, 2012):

- **Mode 1**: Standard charging from a regular socket. Not recommended and even illegal in some countries (1 phase – AC)
- **Mode 2**: Same as Mode 1 but with EV protection in the cable (1 phase – AC)
- **Mode 3**: Standard or fast charging with an EV multi-pin socket (3 phases – AC)

[2] The plan of Source London for infrastructure allocation was to install 25,000 charging points (500 on street, 2,000 in off-street car parks and 22,500 in employer car parks and leisure locations) until 2015, in a way that everyone is located within a mile from a charging point.

- **Mode 4**: Fast charging with special charger technology (3 phases – AC or DC)

The specifications of the different technologies, like approximate charging durations, the power supplied and maximum currents can be seen in Table 2.1. Mode 1 that represents standard domestic sockets without EV protection measures was excluded because its use is not recommended.

Table 2.1: Typical characteristics of different charging modes as defined by the IEC. Reproduced from (BEAMA, 2015)

	Maximum Power Output (kW)	**Example Charging Time**	**Input Voltage (Volts)**	**Maximum Current (Amps)**	**Mode**
AC	2.3kW	8h 20m	230 1-phase AC	10	2/3
	3kW	6h 30m	230 1-phase AC	13	2/3
	3.7kW	5h 15m	230 1-phase AC	16	(2) 3
	7.4kW	2h 35m	230 1-phase AC	32	(2) 3
	14.5kW	1h 20m	400 3-phase AC	21	3
	22kW	55m	400 3-phase AC	32	3
	43kW	30m	400 3-phase AC	63	3
DC	20kW	1h	400 3-phase AC	40	4
	50kW	25m	400 3-phase AC	100	4
	100kW	15m	400 3-phase AC	200	4

Normal charging (Level 1-2/Mode 2-3) has received most of the attention, because it can be performed at home, at the workplace or any other location. The installation cost is lower than for fast charging infrastructure (Level 3/Mode 4) and the duration of the charging process can take up to several hours depending on the initial SOC and the type of each particular station. On the other hand, with fast charging, the vehicle can reach a full SOC in less than an hour and it is a competent complementary solution, especially for emergency situations or long-distance trips that cannot be performed without intermediate charging. Christensen et al. (2010) indicated that in order to accommodate a widespread use of EVs at the future, fast charging infrastructure should be one of the top priorities.

Embedment of communication systems in the charging infrastructure network may require an additional investment, but it offers a significant level of interoperability and various opportunities. Operators may collect charging data, monitor availability and provide information, set the prices dynamically based on demand and design online reservation systems for EV customers.

2.2.5 Modelling of adoption

In the literature, there is a wide interest to understand the preferences for alternative fuel vehicles and to predict their sales shares, within the context of three major modelling techniques: agent-based models, discrete choice models, diffusion and time series models (Al-Alawi and Bradley, 2013). Apart from forecasting future shares that could assist in planning for infrastructure investments, adoption models are crucial to understand the main drivers and barriers for the consumers and propose the appropriate policies.

Agent-based models examine the interaction between decision-making agents like drivers, automakers, policymakers and fuel suppliers and they allow the representation of complex relationships in the market. The purpose of diffusion and time series model is to describe the lifecycle of new products over time and their main advantage is that they can fit the historical trend of this particular product or similar ones.

The theory behind Random Utility Discrete Choice Modelling (DCM) is better explained in Chapter 4 for the purposes of our choice-modelling framework. In the area of adoption, a great variety of DCM methods has been employed. For example, Calfee (1985) found a high valuation of individuals for driving range with the use of the Multinomial Logit (MNL) model. Zhang et al. (2011a) have estimated a Hierarchical Bayes (HB) MNL model using data from a conjoint experiment and one of their findings about electric vehicles was that their high price is the primary reason for their low purchase rate.

Greene (2001) has developed a Nested Logit (NL) model with three levels: the lower level predicts the choice probability of *fuel types* for vehicle with multi-fuel capability, the middle level predicts the share of *vehicle technologies* within particular technology sets and the upper level predicts the choice probabilities of the different *technology sets* (i.e. EV, ICE etc.). Hess et al. (2011a) argued that a simple NL structure could not capture the correlation patterns across the vehicle body types and the fuel types and hence they used a Cross-Nested Logit (CNL) model. Brownstone et al. (2000) estimated a Mixed Logit (ML) model in order to take account of taste heterogeneity around the fuel type dimension. Hidrue et al. (2011)

developed a latent class model in their effort to identify potential classes of individuals that are more inclined towards the purchase of an electric vehicle. A latent class approach was also employed by Parsons et al. (2014), who identified two groups with different sensitivities for various attributes of electric vehicles with V2G capability.

Mau et al. (2008) introduced the concept of *dynamic adoption* for alternative fuel vehicles and they hypothesised that the value of people for HEVs and HFCVs changes as their market share increases. Estimating separate MNL models for four treatment groups, each one provided with different information regarding the market share conditions, they supported their hypothesis about the "neighbour effect".

Finally, we can have *synthetic models* of adoption. Cui et al. (2010) have developed an agent-based modelling framework to analyse the micro-level effect of local PHEV penetration rates on distribution networks. This synthetic framework has three components: a nested logit model to estimate the customer's choice among different technologies, a consumer budget model to estimate the time that the searching process for a new vehicle starts and a bio-inspired mathematical equation to estimate the role of the "neighbour effect" in the decision making.

The estimation and validation of these models[3] are quite challenging for PHEVs and BEVs considering the fact that there was no sales data availability until recently. For the estimation of adoption parameters, a common practice is to elicit driver preferences through dedicated surveys and stated preference (SP) data (Mabit and Fosgerau, 2011). Typically, in these exercises respondents are faced with a hypothetical purchase situation where they have to choose between different vehicles that are characterised by bundles of attributes, like fuel type, operation cost, environmental impact, driving range etc. Some examples of SP surveys for adoption modelling are presented at the end of this chapter.

2.3 Charging Behaviour

In our effort to understand charging demand for EVs, there are several underlying factors that we should take into account. Smart et al. (2010) summarise these factors into the following three interrelated groups: a) driving behaviour, b) charging behaviour and c)

[3] Comprehensive reviews of discrete choice modelling methods and SP analysis in the area of AFV adoption can be found in Dimitropoulos et al. (2011) and in Daziano and Chiew (2012).

available charging infrastructure and vehicle characteristics. This subsection focuses on charging behaviour and what steps have been taken so far, towards increasing the awareness in the electro-mobility community regarding how EV drivers make their everyday charging choices. In particular, the parameters of charging behaviour that are analytically presented are: a) charging frequency, location and "recharge potential", b) battery state of charge (SOC) and range anxiety, c) driving distance, d) driving style and fuel consumption, e) charging infrastructure, f) vehicle mix, g) charging strategies, h) parking choice, i) response to DSM strategies and j) demand for V2G services. In Appendix C, there is a comprehensive classification of the literature based on these characteristics and on charging coordination methods that are discussed in Chapter 5.

Most of the simulations for BEV and PHEV travel and charging patterns use existing data from travel diaries or traffic data based on conventional vehicles (Pearre et al. 2011; Pecas Lopes et al., 2009; Mohseni and Stevie, 2009). According to De Gennaro et al. (2013), the analysis of existing datasets is the key towards exploring the electrification of the transportation sector because mobility patterns could be in their majority quite predictable. Trip distances, route choices and dwell times at destinations are, thus, some of the travel characteristics that are considered to be transferrable from ICE use to the new technologies.

2.3.1 Charging frequency, location and "recharge potential"

The attempts to explain where and when people refuel their vehicles and how this is related to their idiosyncratic characteristics and their travel needs have started several years ago (Dingemans et al. (1986), Kitamura and Sperling (1987)). With the introduction of BEVs and PHEVs in the market, there is a need for drivers to shift from their conventional refuelling behaviour towards plugging-in and charging their personal vehicles for non-trivial stretches of time.

In order to understand charging behaviour, it is important to understand first the role of charging infrastructure. EV charging infrastructure can be characterised by its availability, its location (home, workplace, on-street etc.) and the delivered charging speed (Lin and Greene, 2011). Another important attribute is the "recharge potential", i.e. the spatiotemporal correspondence between a parked vehicle and a charging outlet, which Axsen and Kurani (2008) found to peak between 12am and 6am and to reach a minimum from 10am to 4pm in the U.S. In other words, they found it to be positively correlated with home dwelling periods and negatively correlated with working and driving periods. Morrow et al.

(2008) showed that more than 80% of charging activity takes place between 6pm and midnight while the same peak period for plugged-in vehicles was observed by Smart et al. (2010), with the electricity demand reaching its highest between 09:00 pm and 10:00 pm.

Travel diaries and traffic data from conventional vehicles can be used to synthesise the recharge potential for electric vehicles. Mohseni and Stevie (2009) have used hourly changes in the traffic state to deduce parking intervals. Pearre et al. (2011) also processed ICE driving data to produce a 10-min increment analysis of the parked fraction of their sample fleet. For this study, it is essential to highlight the very high percentage of parked vehicles throughout the whole day, both for weekdays and weekends that is a key point for Vehicle-to-Grid applicability. Moreover, it is noteworthy that the overall pattern differs between weekdays and the weekend, especially in terms of variability and annual minimums.

Spatially, Axsen and Kurani (2008) assume that a parking place has a recharge potential if it is located within 25 feet from an electrical outlet. In the same study it was found that slightly more than half of the respondents have a recharge potential at home, approximately 25% don't have a recharge potential at home but they can find an available charging post for at least 8 hours during an average weekday and another 25% cannot find an available charging post even for this period. Clearly, this distribution is characteristic of the study area (i.e. the U.S.) and it might differ for other countries. For example, the percentage of households with recharge potential is much smaller for London, as it was explained in Chapter 1.

In some studies, travel information is complemented with housing stock data as a means to identify areas with higher adoption levels or home charging availability (Vyas et al. 2007). As a result, there is a need to make preliminary assumptions regarding the frequency and the location of charging events. One approach is to consider that charging times coincide with dwell times (Zhang et al., 2011b). Workplace charging has been modelled as well. Knapen et al. (2012) assume that 10% of the car-driving commuters are using a company car and 50% of those company cars can be plugged-in and charged at work.

Kurani et al. (2007) found that the majority of the respondents plug-in their PHEVs more than one time per day. Some of them also reported that they were plugging-in their vehicles whenever there was an opportunity. In their study, 80% of the vehicles were charged in frequently visited locations, like workplace and home. Other charging locations, reported in smaller proportions, were friends' homes, hotels and other offices.

Smart and Schey (2012) have shown in their results that the mean driving distance between two consecutive charging events for the U.S. is 28.8 miles and that its distribution is quite similar to the distribution of total driving distance per day. This can be attributed to the fact that they charge only once, overnight at home, but the authors avoid this speculation even though the mean number of charging events per vehicle driven day is 1.05. De Gennaro et al. (2013), after applying various charging strategies in their simulation framework for the city of Modena in Italy, have found that the maximum number of charging events per day lies within 0.5 and 2, and it depends on the size and type of the EV.

Apart from increasing the charging availability for sensitive areas, it is crucial to improve the visibility and the viability of existing public infrastructure. Based on drivers statements in Smart et al. (2010), limited out-of-home charging might be associated with lack of knowledge about accessible electrical outlets and with hesitation to plug the vehicle into an unknown charging post without asking for permission. Moreover, some drivers have concerns that plugging the vehicle in public locations might create tripping hazards, or a higher likelihood that the electricity cord will be stolen (Kurani et al., 2009). It is anticipated that with these actions there will be an adjustment of recharge locations and parking choices.

On the other hand, the variation in charges per day is quite wide, showing that different people have a different understanding of their charging needs. Smart et al. (2010) found that people who charge less frequently have a more sophisticated understanding of their driving range and their travel needs and, as a result, they plug-in their vehicles only when it is necessary. Frequent top-up of the battery is possibly associated with a "safety" mentality, from people that want to have the extra SOC in case they need to change their plans and drive for a longer distance. This is inherently linked with "range anxiety" and it might be more intense in areas with low public infrastructure levels.

In Kurani et al. (2009), some people related plugging-in their vehicle with recharging a cell phone, hence not affecting their daily routine, whereas for others it was more of a hassle. Therefore prioritising or incorporating the charging process into the daily routine has a certain degree of heterogeneity and some of the main components of this heterogeneity are: lifestyle and flexibility of working schedule, access to out-of-home charging infrastructure and a combination of range anxiety with the level of understanding about the SOC and the rate of energy consumption.

The charging regimes, of course, are expected to be quite diverse for EV fleets or company cars. The questionnaires from the Smart Move trial in North East England (Carroll, 2010) demonstrated that most of the users charged their vehicles at work whereas only a small percentage preferred home recharging. At the same study, charging experience was rated as quite satisfactory, an important fact for the general acceptance and ease of use of the charging infrastructure.

2.3.2 Battery State of Charge (SOC) and range anxiety

Putting aside charging frequency and location, charging behaviour is also characterised by the initial SOC of a charging event, or, in other words, the level at which drivers usually decide to recharge their vehicle. Smart and Schey (2012) illustrated that EV owners are most likely to start recharging their cars when the battery SOC is between 20% and 80% both at home and in other locations. Sun et al. (2014), analysing only fast-charging infrastructure in Japan, found that the majority of private users start charging their vehicles with an initial SOC of 40%-50% while for commercial users this number is 50%-70%, hence demonstrating a more risk-averse behaviour. Finally, 93% of journeys in the Smart Move trial (Carroll, 2010) have started with a SOC above 50%, showing the reluctance of the drivers to begin a journey with a lower SOC even though the range was adequate to complete it in all the cases.

For PHEVs, the battery SOC plays a great role when it comes to fuel consumption or emission factors. Therefore, their performance is maximised when they start their trips with the battery fully charged, and thus frequent charging events are associated with better performance (Bradley and Frank, 2009). In previous simulation studies, a common assumption is that all vehicles begin the day with a fully charged (100%) battery (Zhang et al., 2011b; Waraich, 2013). A different approach is to combine diary information to estimate the driven mileage of the previous day and data that indicate the recharge potential during the same period (Axsen and Kurani, 2008).

Likewise, it is interesting to have a look at the final SOC after the charging events are over. Smart and Schey (2012) have observed that there is a spike at the distribution around 80%. Since the majority of the participants are Nissan Leaf owners, this can be accredited to the fact that Nissan gives them the option to stop charging when the SOC of the battery is 80%, advising them that this is a decent strategy to preserve battery life if the additional range is not necessary.

De Gennaro et al. (2013) have set both a minimum and a maximum limit for the SOC in their modelling framework (20% and 95% of the nominal battery capacity respectively) arguing that pushing the SOC out of these limits can be damaging for the battery.

In general, people seem to consider the limited battery range as a barrier for adopting an EV, even though empirical evidence proves the opposite (Dimitropoulos et al., 2011). However, it is found that after their experience with the vehicles, range satisfaction is increased and their initial concerns are reduced (Franke et al., 2012a). Consequently, this deviation between subjective and objective reliability to EV range might be caused by lack of driving experience as well as from the inability of the driver to perceive his mobility needs with accuracy. There are two approaches to understand customer preferences for vehicle range: either with the direct statement of their minimum acceptable range or with the use of indirect estimates from discrete choice experiments (Franke and Krems, 2013b).

In the literature, there have been some efforts to quantify the capability of a BEV to satisfy the comfort level or, in other words, the "range anxiety" of its driver. For example, Dong and Lin (2014) introduced the concept of BEV *feasibility*, which is defined as the probability that the ratio of the distance driven between two consecutive charging events and the nominal range of the vehicle is below an acceptable threshold. Knapen et al. (2012) use a more sophisticated representation of BEV feasibility for the whole daily schedule, incorporating energy consumption from the driving intervals and regeneration from the charging intervals. Treating the distance travelled between two charges as a stochastic variable is an effort to reflect the charging choice process of the driver when faced with alternative charging opportunities. With this approach, though, it's not possible to model some of the critical factors that affect charging choices like electricity price or location.

Range anxiety has been indirectly modelled by Sun et al. (2014), with the use of a stochastic frontier approach. The density of fast-charging infrastructure has been used as a proxy in order to examine the relationship between the remaining SOC before a charging event and the anxiety related with charging availability.

EV manufacturers, policy makers or other stakeholders cannot rely only on the actual driving needs to decide on the vehicle or network characteristics. It is anticipated that drivers will opt for a surplus range over their daily mileage either because of a safety ("just-in-case") mentality as mentioned earlier or to avoid driving their car below certain levels of SOC. After interviews with EV drivers, this extra battery capacity, which is known as "*range* *buffer*", was found to be around 20 miles (Turrentine et al., 1992). Likewise, Franke et al. (2011) used a game to assess the range comfort zone of the drivers and revealed that they are not willing to use more than 80% of the vehicle's range.

The dynamics of range attitudes and control strategies for EV drivers have been also examined from a psychological perspective. Franke and Krems (2013a) presented a conceptual framework where individuals self-regulate the use of range resources based on three psychological reference values:

- **Competent range**: This is the maximum range that an EV driver is able to achieve, given the information on his range-maximising efforts.
- **Performant range**: Lifestyle and habits don't allow individuals to always reach competent range and, thus, this a lower reference value representing their typical available range
- **Comfortable range**: This is the range buffer mentioned above and it can be elicited either by directly asking the drivers to provide the value, or indirectly through observing the stress levels caused by different buffer levels. Otherwise, it can be described as the balance between mobility needs and mobility resources.

In a later paper, they used this self-regulation control loop that they have created in order to explain the charging behaviour of individuals (Franke and Krems, 2013c). More specifically, they found that this "psychological interaction" might explain the variance in the SOC level, which triggers the initiation of a charging event.

Range limitations add a risk dimension[4] to the recharging behaviour. Since individual attitudes to risk vary significantly, unless they are quantified, it is difficult to understand the complicated patterns of charging frequency or initial SOC before a charging event. Sun et al. (2014) detect two types of risk management regarding mid-trip fast-charging choices: a) Risk-averse drivers who will choose a higher SOC in order to reduce the risk of running out of battery and b) Risk-seeking or adventurer drivers who will charge only if the remaining SOC is not adequate to guarantee the rest of the trip. For example, the Smart Move trial

[4] If for any reason, the SOC of the vehicle is not adequate to complete a trip, the driver will have to make a detour in order to find a charging station. In the worst-case scenario, he will have to find a substitute car or contact the emergency roadside services. It is interesting that EV manufacturers have started to take actions for these extremes scenarios by providing complimentary roadside assistance and access to rental cars.

(Carroll, 2010) has indicated a significant effect of range anxiety, with drivers being more cautious than required and the maximum length of the performed journeys being 25% of the average vehicle range. In order to optimise the density of highway fast-charging infrastructure, planners should find an intermediate balancing solution between the two extreme users.

2.3.3 Driving distance

Even though the focus of the chapter is to understand charging behaviour, we can't simply ignore the driving needs of an EV owner, since charging is strongly interrelated with travel behaviour. One frequently anticipated question is how much people are driving every day, either in urban or rural environments and if the battery range of an EV is adequate to cover these needs. The majority of studies about EV market acceptance neglect these travel-induced requirements and they are oriented around social, market and customer beliefs (Pearre et al., 2011). Based on Gondor et al. (2007), more than 95% of daily driving in the St Louis metropolitan area is feasible with a 100-miles electric range. Also, in Great Britain, 95% of the trips are below 25 miles and hence are comfortably within a BEV range (OLEV, 2011). However, it is doubtful if an average daily profile is adequate to describe drivers' needs or the implications of occasional long-distance trips.

While researchers usually discuss the effects of driving behaviour on charging demand, the direction of causality is not straightforward. The charging choices and the attributes of an electric vehicle are just as likely to influence driving patterns. Tal et al. (2014) show that there is a correlation between Vehicle Miles Travelled (VMT) and the type of EV, with PHEV users driving on average more than BEV users. Nissan Leaf drivers are reported to drive 40% more than the European annual average mileage for a traditional ICE (10,307 miles compared to 7,170 miles) (GreenCarGuide, 2015).

Some authors argue that average travel data is not adequate to capture charging behaviour and variation needs to be examined both within a day and from day-to-day (Lin and Greene, 2011; Vyas et al., 2009). In particular, Vyas et al. (2009) suggested that by ignoring the variation in daily mileage, electricity consumption for PHEVs is overestimated at the expense of gasoline consumption being underestimated. The results in Franke and Krems (2013b) suggest that there is a necessity for multi-day instead of single-day travel data collection in order to be able to provide meaningful estimates of range preferences.

This variation in daily mileage as a means to understand the extent to which BEV ranges are sufficient for everyday needs, has been treated occasionally with the use of parametric probabilistic distributions like the Weibull distribution (Traut et al., 2012) or the gamma distribution (Dong and Lin, 2014) and calibrated with the assistance of GPS travel data.

With the availability of long-term longitudinal travel data, it is possible to synthesise annual distributions of daily-driven mileage. In some studies, these curves are used to isolate long-distance trips and estimate the proportion of days throughout the year that various EV technologies can cover travel demand without the use of out-of-home charging infrastructure (Pearre et al., 2011). For those days of the year that an adaptation in behaviour is required, the question that arises is what the alternative options are. Some of the potential answers are: a) shift mode to a secondary conventional vehicle or public transport, b) reschedule plan to reduce the additional mileage or c) seek alternative charging options throughout the day.

2.3.4 Driving style and fuel consumption

A common assumption is that driving behaviour will remain the same for the new vehicle types. This is somewhat unrealistic if we consider that some people will adjust their driving patterns in order to maximise their savings from electricity consumption. For example, quantitative data from an EV trial in the UK (Carroll, 2010) suggest a negative correlation between driving efficiency (km/SOC) and braking regeneration for the smart Fortwo EVs. As a result, a more predictive driving with less acceleration and braking events could lead to energy savings and increased range. Moreover, in the same study, journey efficiencies were improved for low SOC, indicating the existence of range anxiety and that drivers could successfully modify their driving under pressure. Yet, since there is no clear evidence on what the behavioural change will be, accepting the current driving style is a practical solution that can be employed for predictions and policy implications.

Charging behaviour is fundamentally different between BEV and PHEV drivers. First, the dual fuel option that PHEV offers turns their owners to be more sensitive to electricity and gasoline price signals than BEV owners are. Moreover, PHEVs are functional with a considerably smaller battery size than BEVs and hence, their requirements in terms of charging duration are lower. In the same direction, Reddy and Linden (2002) suggest that there is a higher likelihood for PHEV manufacturers to use more advanced materials for their batteries which will affect their charging method, consequently decreasing charging duration.

For example, charging frequency for PHEV drivers is a matter of cost efficiency, especially in a context of rising gas prices. Plugging-in regularly could reduce the need to drive in a charge-sustaining mode, hence resulting in fewer GHG emissions and economic savings for the driver. According to Kurani et al. (2007), even if drivers are not capable of quantifying the fuel-savings and comparing them with the high upfront costs of the vehicle, only the idea of saving money is enough to motivate them to drive in the electric mode.

EV simulations have demonstrated that fuel consumption is highly dependent on several parameters such as charging scenarios, charging rates and distribution of battery capacity for the examined fleet. According to Zhang et al. (2011b), larger batteries could contribute to the fuel-saving benefits that out-of-home recharging creates. Then the modeller can either add a certain degree of complexity by integrating the driving style with fuel consumption levels, or assume that fuel consumption (kWh/miles for BEVs or combined kWh/miles and mpg for PHEVs and blended operation) has a constant rate that is defined by the vehicle type, like Axsen and Kurani (2008) do.

Alternatively, consumption could be modelled with the use of actual driving cycles in urban areas (Waraich, 2013; Smith et al., 2011). These cycles, otherwise known as duty cycles, can be constructed with the use of multivariate statistical analysis of trip characteristics and intensity of vehicle usage. Weather and climate can have significant effects on duty cycles and battery performance, not only directly through the efficiency of the battery under different temperatures but also indirectly through traffic congestion and large variations of speed and acceleration.

In-vehicle instrumentation can provide EV and PHEV drivers with valuable information and help them to optimise their vehicle's performance. In Kurani et al. (2009), an Energy Monitor system was providing the users with constant information about their fuel consumption, a fact that improved their awareness of the relationship between the vehicle's performance and their own driving behaviour. In some cases, this even worked as a stimulus for a friendly competition between the members of the household regarding the fuel economy that they achieve when they drive.

Out-of-vehicle interfaces, accessible to the users, can also have substantial effects on their combined charging and driving behaviour. For example, web-based pages linked with their vehicle's on-board logger could maintain a personal historical database with locations, recharge timing, rates, fuel economy and other valuable information. However, these interfaces should be user-friendly and designed in such a way that they attract the drivers to get involved and not discourage them due to their complexity.

Drivers' behaviour is certainly not static, and it dynamically evolves through a day-to-day learning process especially for early adopters. Users get accustomed with the vehicle itself, its driving style and last but not least with the refuelling process. PHEV owners have reported modifying their driving speed, their acceleration and their charging frequency after useful feedback from in-vehicle and out-of-vehicle interfaces (Kurani et al., 2009). Driver assistance systems can accelerate the learning process especially by alleviating range anxiety (Franke and Krems, 2013b). Apart from the experience that drivers gain, the technological advancements of their surrounding environment (e.g. the continuous dissemination of charging infrastructure) is also likely to alter their charging choices in a dynamic way.

2.3.5 Charging infrastructure

For plugged-in vehicles, charging rates are conditional on the infrastructure, the onboard charging hardware and the energy storage system. For example, charging rates normally vary for different battery chemistries. EVs have been designed in such a way that they can plug-in and draw power from dedicated infrastructure and typical household outlets (Bradley and Frank, 2009). Circuit levels and amperage levels, therefore, affect charging rates and consequently charging durations.

Lemoine et al. (2008) assume that for a regular 110-120 V outlet, PHEVs will have a minimum charging rate of 1kW. At the same study, charging efficiency i.e. the proportion of the energy that reaches the vehicle's battery related to the energy that comes from the electrical outlet is 83%. Kang and Recker (2009), in their simulations, use standard charging infrastructure (120V/15A) and upgraded (level 2) charging infrastructure (240V/40A) with respective charging efficiencies of 82% and 87%. Knapen et al. (2012) assume that there are two charger types (3.3kW and 7kW) and that the specific type available for each household is dependent on the EV size. In Mullan et al. (2011), EVs charge with the standard 10A home electricity supply and each vehicle consumes 1.5kW power from the grid for the whole charging duration. De Gennaro et al. (2013) assume a relatively higher charging efficiency of 95% and they employ two charging rates: 2kW (Mode 1/2) and 40kW (Mode 4) to represent the charging infrastructure of Modena, Italy.

One question that is raised is what the behavioural impact will be from the deployment of fast charging infrastructure. CHAdeMO Association (2011) reports the changes in charging choices after the installation of public fast charging units in Tokyo. The effective range of the vehicles has increased by a factor of seven, indicating that range anxiety has been significantly limited. Drivers allowed the SOC of the battery to drop below 50% before they plug-in their vehicles, unlike the pre-installation period when they had the psychological barrier of not reaching their destinations.

2.3.6 Vehicle mix

The number of distinct vehicle types used in a simulation might affect several performance measures like emission factors or net impact on the power grid. Likewise, it might affect the distribution of charging choices and as a result, a larger variety in the vehicle mix is more likely to produce more realistic scenarios. For example, Waraich (2013) includes only PHEVs with a maximum battery capacity of 10kWh in his simulation, and hence he projects a lower energy demand compared to a scenario with BEV penetration in the market. Likewise, Acha et al. (2012) use the Nissan Leaf as the EV unit in their simulation for simplification reasons, assuming thus no variation in battery capacity, energy consumption and charging rate.

Instead of using specific EV models, a few studies have performed a classification of the simulated fleet (i.e. small, medium, large) based on the vehicle size (Knapen et al., 2012; Perujo and Ciuffo, 2010; De Gennaro et al., 2013). In Knapen et al. (2012), a Bayesian network links these classes to battery range and energy consumption values through a map of conditional probabilities that leads to the aggregated power demand for the network. Koyanagi and Uriu (1997) base their energy consumption scenarios on the distribution of different-sized registered vehicles in Tokyo, capturing in this way the heterogeneity of the vehicle mix. In their analysis, apart from private vehicles, they include buses, taxis and company cars and they take into account the operational features of each type when they synthesise charging and discharging patterns. Finally, Galus et al. (2012) integrate their power system and mobility framework with a sophisticated vehicle technology simulator, which can provide mixed fleets of various fuel technologies and predict the energy demand within these fleets.

Policy or scenario-based analysis requires an initial prediction or assumption regarding the penetration rate of EVs in the market by the year of interest. One might examine the extreme scenario, where all vehicles are replaced from BEVs or PHEVs. Then different levels of adoption can be investigated separately and a sensitivity analysis could demonstrate the critical points where the existing infrastructure starts to be inadequate. For example, Koyanagi and Uriu (1997) analyse five scenarios with varying EV shares across vehicle types.

2.3.7 Charging strategies

Charging strategies vary in the literature. There is immediate charging (or *dumb or uncontrolled charging)* if the vehicle begins to recharge as soon as it's plugged-in and the electricity price remains constant for the whole day. In disaggregate modelling approaches, uncontrolled charging typically lasts until the end of the person's activity, while in aggregate models the assumption is that by the end of the charging period vehicles have a full SOC. Other suggested strategies are:

- *Delayed charging,* when the charging event is shifted so that its end time coincides with the starting time of the next trip (Zhang et al., 2011b).
- *Average charging,* when the vehicle charges with the minimum constant rate required to reach a full battery level using the whole dwelling period. (Zhang et al., 2011b).
- *Uniform Low Cost,* when there is a uniform distribution of the charging event across the lower tariff period so that the driver minimises his cost (Knapen et al., 2012).
- *Optimal charging,* when the allocation of charging events is optimised so that the system load curve is flattened in the best possible way (Lemoine et al., 2008). For this scenario, charging events of individual vehicles don't need to be continuous and they can be interrupted throughout the dwelling period.
- *Restricted charging,* when charging is allowed only during particular periods of the dwelling period (e.g. from 10:00 pm through the next morning to avoid additional burden to the peak load) (Kang and Recker, 2009).

With respect to location and time-of-day, charging scenarios have been categorised as:

- "*Home-Only"*, when all drivers plug-in and charge their vehicles as soon as they return home from work (Lemoine et al., 2008; Pearre et al., 2011; Khan and Kockelman, 2012; Mohseni and Stevie, 2009; Kang and Recker, 2009; Knapen et al., 2012; Mullan et al., 2011).
- "*Enhanced Worker Access*" or "Home and Work", when apart from home there is charging availability at workplaces (Axsen and Kurani, 2008; Flath et al., 2013).

- *"Twice Per Day"*, which is similar to the previous charging scenario since there is charging availability at work but it is assumed that all drivers charge as soon as they arrive either at work or at home (Lemoine et al., 2008).
- Home as main charging location and other specific locations as potential fast-charging opportunities (Nicholas et al., 2012).
- "*Off-peak only*" or "Early Low Tariff", when it is assumed that the appropriate incentives are introduced so that charging demand is shifted from congested day intervals to non-congested ones (Axsen and Kurani, 2008; Knapen et al., 2012).
- "Not every day", when drivers do not have a regular daily pattern for charging their vehicles, but they charge them only when it's needed (Perujo and Ciuffo, 2010).
- "Any time charging", which is an ideal scenario where all parking locations have a charging station available (Mohseni and Stevie, 2009; Kang and Recker, 2009).

Summarising, the charging strategies listed above can be classified based on three main directions: the location (only home or combination of home and out-of-home charging places), the starting time of the charging event (immediately after plug-in or later) and the level of "intelligence" of the suggested operation, i.e. if it is optimised with respect to some specific outcome (e.g. cost or network constraints). As it can be seen in Figure 2.2, this is a nested classification and some of the strategies can belong at more than one nest.

2.3.8 Joint parking and charging behaviour – Insights from the parking demand literature

Parking is intrinsically related with charging behaviour and the inability to charge at home might create additional problems and scheduling challenges for the individuals. For company cars and charging opportunities at the workplace, the scheduling requirements are still moderate. In any case, it is sensible from a policy perspective to analyse future EV sales jointly with housing stock developments and estimate the anticipated proportion of EV owners with recharge potential at their home. This sort of analysis could build a new basis for the spatial design and allocation of future charging infrastructure, driven not only from the spatial distribution of EV sells but also from the availability of parking places.

In the UK, the maximum level of off-street parking provision for residential users is recommended to be 1.5 spaces per house (Marsden, 2006). Planning for the promotion of public transport should lead to a lower provision level for areas with better public transport links. Table 2.2 below shows an estimation of residential private parking availability in the

UK and overnight storage location. It is evident that the high percentage of street vehicle storage and hence the lack of private space for London residents (42%) could be an obstacle for EV adoption.

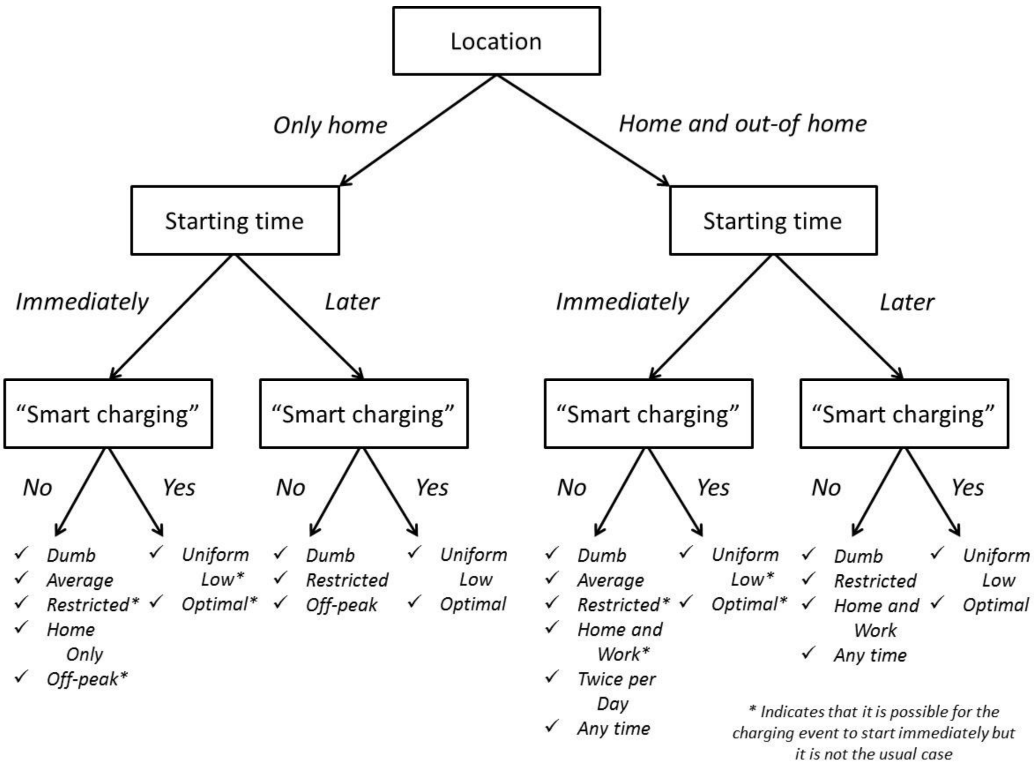


Figure 2.2: Nested classification of charging strategies that have been used in modelling studies

Before attempting to jointly model charging and parking preferences for out-of-home locations, it is critical to understand parking policies and the effects they have on travel behaviour and the demand for parking, as they have been portrayed in transportation literature.

Table 2.2: Patterns of overnight vehicle storage in the UK. Reproduced from (RAC Foundation, 2004)

Where parked	London (%)	Other Urban (%)	Rural (%)	All areas (%)
Garage	15	24	30	24
Private property (not garaged)	40	48	55	49
Street	42	24	12	23

Parking policies, if implemented properly, can effectively alleviate congestion. As a result, they can contribute to the reduction of emissions, better urban design and wider economic and social development. On the contrary, inappropriate parking policies may lead to undesirable outcomes, like illegal parking, lower safety levels or excessive searching times.

For local governments, one of the main objectives of applying parking policies is to generate revenue that will be used to cover other costs (IHT, 2005, p.64). Most of the times, however, the "right conditions" do not exist and not everyone pays the true cost of their parking (Shoup, 1997). Under-pricing on-street parking makes it more attractive than off-street solutions, but it creates a shortage along with other traffic-induced disadvantages (Shoup, 2006). Parking price is affected by its supply and reducing off-street spaces has an adverse result: their prices are increased and in combination with lower prices for on-street locations, cruising for parking is incentivised.

Charging employees for parking at their workplace has also been discussed as a means of traffic management and car use reduction (Rye and Ison, 2005 [5]; Willson and Shoup, 1990). It has also been suggested from the UK government to local authorities as a policy to be considered for future planning (Department of the Environment, Transport and the Regions (DETR), 2001). In central London, like in many other urban centres, there is a high percentage of commuters that can park for free near their workplace (80% according to the National Economic Development Office (1991)), thus encouraging the use of car at peak hours. Willson and Shoup (1990), among others in the literature, demonstrated that the introduction of parking fees for commuters could have a significant effect on travel mode choice. In practice, parking charges at the workplace are not very common and they are encountered mostly in the public sector and less in the private sector.

As one might expect, there are several difficulties and barriers with promoting policies that would allow the pricing of parking at workplaces. They are in general quite complex to overcome, and this level of complexity can considerably vary from private to public

[5] Rye and Ison (2005) summarise some of the key elements from pricing structures at workplaces in the UK, hospitals and universities in their majority. Typical charges for employees and staff are between 50p and £1.50, with no differentiation (basic price per day or per month) or little differentiation (e.g. based on income bands), and parking fees are usually deducted from their payroll. In some universities, user segmentation was attempted by providing higher quality and availability certainty to regular users or to users that were willing to pay for it.

organisations. The same difficulties and barriers would apply in pricing the electricity for employees that want to recharge their EVs at the workplace. Below the problems and the required strategies are summarised (Rye and Ison, 2005):

- Sensitive issue for industrial relations and risk of opposition. Proper consultation is required as well as transparent measures with equal treatment across staff members
- Lack of motivation if objectives are not clear. Organisations should set clear and acceptable objectives (e.g. improvement of the facilities, safety, "green" policies)
- Inequalities between staff members. The charges must fluctuate at low levels, potentially varying based on the income range and exemptions should be provided for special cases.

Parking policies cause a behavioural response especially concerning the choice of parking type and parking location. There are several dimensions to these decisions and here we cite and explain the effects of some of the most important variables that have been analysed in parking choice modelling literature: cost, duration, egress or walking time, cruising or search time and parking availability.

Drivers do not always have knowledge of the **parking prices**. Depending on their willingness to pay, they could reach close to their destination and then start searching, or park their car at the first parking place available without making any comparisons, if its price is low. Kelly and Clinch (2009) have estimated the temporal variance of price elasticities for on-street parking and have found values in the range of -0.15 to -0.61 with the highest being at 9am and the lowest at 12pm. This is also the only study that examined the effect of price on parking duration, finding a 16.5% decrease of average parking duration after a 50% increase in parking fees. Ottosson et al. (2013) go a step further by estimating the price elasticity of on-street parking demand by time-of-day and by city block, thus creating the opportunity for parking fee optimisation in a highly granular spatial level.

Parking choice can also be influenced by **parking duration** or by the length of stay at the destination. Time limitations are sometimes enforced to discourage drivers from occupying a parking place for many hours, yet, these enforcements can usually lead to time limit violations or illegal parking acts. Golias et al. (2002) have shown that longer parking durations make off-street options more attractive even though, normally, they should make higher searching times more acceptable. One of the explanations for this result could possibly be the fact that price structures for off-street facilities are advantageous for longer parking durations.

Walking time from the vehicle to the final destination location and the disutility associated with it has concerned several researchers in the past. For example, Shiftan (2002), studying the behaviour of commuters in Haifa of Israel, reported the following numbers: 47% of drivers walk up to 5 min, 39% walk between 5 and 10 min and only 14% walk more than 11 min. Estimating the willingness to walk in order to save money or even find free parking is of great interest both for public sector and private parking facilities. Theoretically, the longer the distance is, the higher the probability for drivers to look for a more expensive parking place or shift to public transport. Additional factors, like safety perception in an underground garage, might cause a further reduction of the willingness to walk. In any case, exceptions could exist for individuals that gain positive utility from longer walking distances because they consider walking as a positive part of their trip (Marsden, 2006).

Apart from walking time, when looking for a parking place, drivers spend some **cruising time** that has its own indirect costs (time and fuel). The value that an individual assigns to this time depends on several factors, e.g. income, weather conditions, safety etc. The value of time obviously varies from one individual to another, but it can also vary for the same individual under different circumstances. Even during the same trip, if the probability of being late at your destination increases as you cruise, or if fatigue has a negative effect on your psychology, it is possible that your value of time will change. Moreover, there is great uncertainty regarding the outcome of parking search because the proportion of the traffic that is in a searching state is unknown. The problem with cruising for parking is that delayed times are incurred to all drivers, even those that are not looking for a parking place. Shoup (2006) estimates the elasticity of search time with respect to several variables and we present here two results that are thought-provoking for future research in the area of EVs:

- The elasticity with respect to *parking duration* is +1, which means that drivers with longer stays are willing to spend more time to find a curb space. Since charging events are by default time-consuming, are EV drivers willing to spend more time to find a charging post and how is this balanced with the limited range of their battery?
- Searching time is relatively inelastic to *fuel price*. What happens for PHEVs that have two alternative fuelling options? And what happens when recharging price depends on the location (e.g. on-street free charging compared to electricity tariff at home)?

Parking search has received special attention in the literature (Polak and Axhausen, 1990). It is considered as a sequential process where drivers find a parking place and evaluate its attractiveness along with the probability of finding a more attractive place if they keep driving. Their subjective estimate of this probability depends on their experience of traffic and parking conditions in the area at this time of the day. Questionnaires and focus groups could offer preliminary information on the searching strategies that drivers apply under different circumstances (e.g. circling, directed search for on-street parking, parking in off-street spaces etc.) and it would be interesting to examine if these behavioural routines are prone to change under the limitations of electro-mobility. Understanding and modelling parking search behaviour is quite complex: first, it can be easily altered by traffic conditions and by the psychological status of the driver and second it's difficult to place it in a temporal context due to the latency of the search starting time (Montini et al., 2012) [6].

Finally, **parking availability** has a strong effect on travel behaviour, especially on mode choice, where the difficulty in finding a parking spot might be more important than an increase in price (Golias et al., 2002). The role of availability is also significant in parking search behaviour. When drivers approach their destination, they have some information regarding the parking types in the area, their prices, their locations etc. Nevertheless, even in the extreme scenario that they have perfect knowledge of the parking options, there is still an uncertainty about the outcome of the searching process, because it is always dependent on the instantaneous availability (Polak and Axhausen, 1990).

The trade-offs that drivers make for parking choices are quite difficult to analyse only with the use of real-world data due to the magnitude of available options. In addition, some of the examined attributes like walking distance, access time and price might be correlated in a revealed preference context. Subsequently, numerous studies have adopted stated preference techniques to elicit drivers' preferences for parking alternatives (Golias et al., 2002; Shiftan, 2002). Of course, for the same reason, these studies come with a limitation to the range of options that is provided to the respondents (Axhausen and Polak, 1991). Looking for other parking options, changing the mode of travel or adjusting departure time are some of the most recurring alternatives in these studies when drivers make their trade-offs.

[6] The authors argue that the starting time of the search process is biased when estimated from survey questions and that the existing practical assumptions to approximate it have certain drawbacks. Their approach is to use a spatial proxy with the assistance of GPS data and we believe that joint analysis of similar datasets with survey results could significantly improve the behavioural analysis in this area.

Parking behaviour is characterised by a certain degree of heterogeneity, with different segments of the population having different perceptions. Such differentiation might be triggered from the purpose of the activity at the parking destination and the flexibility that it entails. For example, shoppers usually don't exhibit the same behaviour with commuters. Additional options like changing destination, changing frequency or time of visit and changing activity duration illuminate why shoppers are by nature more flexible and less restrained by parking policies than commuters. Evening residential parking is in turn more constraining than parking for commuters because it leaves drivers with no other choice than to find an overnight place (Benenson et al., 2008). In their survey, Hess and Polak (2004) have identified four journey purposes: full-time work, part-time work, shopping and errands.

Ranking the attributes of parking choice, based on user sensitivity, Axhausen and Polak (1991) found that respondents are more sensitive to walking distance, followed by parking search time and in-car access time respectively. Generalising, the evidence shows that out-of-vehicle costs (e.g. parking prices and walking times) are more important for the drivers than in-vehicle costs. However, individual valuations for parking characteristics might differ (Hess and Polak, 2004) and sensitivities are likely to vary for different locations and different journey purposes.

Having described the explanatory variables of a representative choice model for parking, what are the alternative options for the drivers and how is the *choice set* synthesised? In the case of parking types we usually encounter the following:

- **On-street parking** (free or metered)
- **Off-street parking** (ground parking lot or multi-storey facility)
- **Illegal parking**, as it is specified by the local regulation

or if we examine them based on their accessibility to the users (Waraich and Axhausen, 2012):

- **Public**: accessible to all users
- **Private**: accessible only to some users (e.g. residents, employees, shoppers etc.)
- **Reserved**: accessible to selected users (e.g. disabled or online reservations)
- **Preferred**: accessible to users with certain characteristics (e.g. parking places with plug-in availability for EV drivers)

Of course, a parking place could be characterised as a combination of the two classifications (e.g. on-street public parking) or even of two types within the same group (e.g. reserved charging post).

Several studies have employed discrete choice methods to **model parking type or location choice** in the past. Teknomo and Hokao (1997) use the MNL model to explain parking location choices. Hunt (1998) applies an NL model for a combined analysis of parking type and location. Bradley et al. (1993) also model the effect of parking policies on mode and parking type choices with the use of NL. Finally, Hess and Polak (2004) capture random taste variation in parking type choice with the use of a mixed logit model.

Alternatively, some authors have tried to simulate the disaggregated preferences of drivers for parking characteristics with *agent-based models*. In Waraich and Axhausen (2012) a hierarchical parking choice algorithm is applied with two decision levels: a first one that is based on the eligibility of the agents to access the parking supply, and a second one where the agents evaluate the remaining parking options from the first level based on a utility function. The PARKAGENT model (Benenson et al., 2008) employs rule-based techniques to simulate several aspects of the parking behaviour (driving, searching parking and leaving) by explicitly integrating these choices within a spatial context to dynamically represent traffic and parking states and examine the change in behaviour with varying exogenous conditions.

Until now, parking choice was presented as a rather static phenomenon, ignoring in this way the interaction that it can plausibly have with departure time choices. Activity scheduling and travel choices are in reality *time-dependent* and the varying parking attributes throughout the day might have broader effects on travel behaviour, rather than just a change in parking type or location: departure time choice or parking duration are typical examples. Increased parking fees during rush hours can result into shortened parking durations, earlier or later departures from trip origins and consequently they might cause modifications in activity timings (Lam et al., 2006)[7].

Another aspect of parking behaviour that has a dynamic character is the *adaptive choice* of the driver when parking lots are congested. Van der Waerden et al. (1992)[8] developed a

[7] The modelling approach in this study is based on a hierarchical choice structure: joint modelling of departure time and parking duration with the MNL model on top, followed by the choice of parking location that minimises the users' disutility for the particular time interval.

[8] Queue length, expected waiting time and searching attempts before making the choice were some of the explanatory variables that they employed for their polychotomous logit model.

stated choice exercise to model how people behave under these circumstances, giving three alternative options to the respondents: drive to another parking place, wait or park illegally.

In order to make well-informed parking choices, there is a need for **information** and in particular for occupancy data, not only for garages and parking facilities but also for roadside spaces (Mathur et al., 2010). The former is relatively straightforward with the installation of in/out counters at the entry and exit points of the facility and with their display near the garage or at neighbouring roadways. The latter is more challenging and it can be done in two ways: fixed and mobile sensors[9].

Afterwards, this information could be disseminated to the drivers in the form of a suggestion for an available parking place, through a smartphone or a navigation device. It might be also distributed to the Internet in a similar manner with traffic congestion information websites.

Moreover, real-time parking information is useful for private operators and municipalities who are in charge of parking management. Using only parking meters and pay stations, they could implement performance-based pricing techniques and adjust locational prices based on occupancy levels. Shoup's (1997) target with these price adjustments was to achieve 85% occupancy for each block. Municipalities, in particular, could use this information to improve the effectiveness of parking enforcement.

What is the effect of this information on travel and parking behaviour? Acquiring information, either passively or actively, is undoubtedly a critical factor of decision making for many aspects of our everyday lives. Travel decisions and in particular parking choice cannot be an exemption. Khattak and Polak (1993) showed that the propensity of being affected by information in parking choices increases with increased "objective" knowledge and decreases with increased "subjective knowledge. In other words, drivers that are more aware of exogenous parking conditions are more likely to consider this information compared to drivers that believe they have a better knowledge. Furthermore, the likelihood of an individual to effectively store this information in his memory for future use is strongly interrelated with his demographics and his personal attitudes towards information acquisition. The mixture of idiosyncratic characteristics and existing knowledge of the system can determine the willingness to seek for synthetic information (static and real-time)

[9] *Fixed sensors* can be installed in the asphalt or in parking meters and detect occupied parking locations. Their drawback is the huge upfront and operational cost, especially for large scales of parking monitoring. *Mobile sensors* can be attached to moving cars (preferably taxis or governmental vehicles to downgrade the cost) in order to report distances from obstacles and GPS devices mark the respective coordinates.

and rely on it. Vice versa, Khattak and Polak (1993) have demonstrated that the sources of information that someone uses have a significant effect on the knowledge they have of parking conditions and hence on their parking behaviour.

Information and Communication Technology (ICT) availability and parking information are of great value to the drivers and the traffic system as a whole, but going one step further, ideally we would like a **spot reservation system**[10] where customers could reserve a parking place before they even reach their destination. The *benefits* from such a system are numerous:

- Eliminate the uncertainty of finding a parking place and the disutility associated with searching times
- Relieve traffic congestion
- Reduce noise, CO_2 emissions and other pollutants
- Enhance traffic management and facilitate operators with better predictions of parking demand

Online parking reservation systems are already applied in various contexts, from downtown to airport and rail station facilities. However, there are undoubtedly *difficulties and side effects* from their implementation:

- They require exact knowledge of parking occupancy and thus vast investment in monitoring technology
- They entail that the rest of the vehicles are notified about the reservations and do not violate them
- They may lead to operational issues if users reschedule without notifying or if they are late on the pre-agreed time

2.3.9 Response to demand side management – Insights from the residential energy demand literature

Time-of-day recharging is probably the most interesting aspect of charging behaviour, essentially due to the impact of additional energy demand on the electricity grid. Intuitively,

[10] Alternative emerging markets for parking reservation have their foundations in sharing economy. Owners of parking spaces, like households with available garages can offer reservations to other users of the system (e.g. JustPark) and drivers occupying public spaces can get notified if someone is looking for parking and sell them their "asset" (e.g. MonkeyParking). However, the latter has not come without protests and accusations for its legitimacy (Rall, 2015). JustPark extended the reservation system to electric vehicle users, by cooperating with OLEV and Chargemaster in order to provide homeowners with free charging infrastructure.

without time-of-day electricity tariffs, EV drivers will choose to recharge their vehicle at a time that maximises their own utility. Since most of them are either unaware or unaffected by the fact that they incur extra costs when they charge during peak demand periods, a behavioural shift needs to be established through demand side management methods.

Apart from the time-of-day, the electricity tariff for recharging an EV may also vary based on the location. For example, there are several cities worldwide where drivers can plug-in their vehicle at public charging posts and top-up their battery for free, while the cost for home charging depends on the local retailer and their household's electricity bill. Consequently, the recharging price is an important parameter for charging choices. Tal et al. (2014) suggest that some of the drivers in their study avoided charging their car at home due to the high cost of electricity. In Schey et al. (2012), time-of-use tariffs influence participants who shift their charging activity to the starting point of the off-peak period, causing in this way unintended spikes at another point of time.

One major problem with electricity prices is that consumers find their structure complex and they are not completely aware of the energy-related choices they make. A survey from IBM in 2011 revealed that 30% of the consumers did not understand the basics of their energy bill (IBM, 2011). Although this applies for energy consumption at home (e.g. use of appliances like air-condition or washing machine) one might argue that this behaviour is transferrable to EV charging choices. Therefore, exploring the factors that affect household energy consumption patterns and the individual load profiles that are shaped from this behaviour could generate valuable insights on EV recharging and the users' response to electricity tariffs.

Yao and Steemers (2005), classify the determinants of home energy demand for the UK in two groups: a) Behavioural determinants or "human factors" that are associated with the relationship between electricity use and preferences or habits of the end user (e.g. frequency of use per appliance) and b) Physical determinants that are constraints from the environment, like climate or building design. Both groups are more or less influenced by occupancy patterns including the number of residents and the time that they spend at home. Combining resident occupancy models and energy consumption models for distinct home appliances and taking into account the heterogeneity and variability in time-of-use it is possible to create representative household load profiles and predict electricity demand.

Nevertheless, when it comes to domestic appliances, usually consumers are poorly informed regarding their consumption levels and, as a result, it is difficult to relate their individual profiles with behavioural patterns. In order to increase awareness and potentially shift consumers' perceptions towards a more efficient energy use, it is essential to provide detailed information both in pricing arrangements and in consumption rates and at the same time to keep a relatively low level of complexity so that they are not demotivated. Smart meters can deliver this information and help consumers make the right choices when electricity tariffs do not remain constant. Moreover, in-home smart appliances could automatically react to external price signals, enabling demand side management with little or no effort from the consumer side.

But what is the response of individuals to complex price signals and imperfect information situations? Bonsall and Shires (2005) suggest that consumers, in general, prefer simplicity in pricing designs, but they are willing to accept and respond to additional complexity if the structure of the prices is clear and logic. This preference for simple tariffs is more constraining for highly competitive markets like telecommunications than for monopolistic goods like road pricing. When it comes to complex choices, where people do not have all the information available or do not have the time or the analytical skills to process this information, typically they employ heuristics in order to come to a decision (Darke et al., 1995). Their attitude towards uncertainty and their willingness to engage in order to gain a better knowledge of the system are probably the most important parameters in this process. Representative steps of a heuristic to respond to complex price schemes can be seen in Figure 2.3.

Dynamic pricing of electricity is one form of complex price signal. The main concept is that the price per kWh dynamically varies either by the time-of-day or by the load at the household level or a combination of the two factors (Dütschke and Paetz, 2013). The role of dynamic pricing for the electricity supplier and the different pricing programs that can be applied are thoroughly discussed in Chapter 5. Here the focus is on the consumer side.

Understanding demand response[11] to the dynamic pricing of electricity is essential to electrical utilities, especially taking into account the expected additional loads from EV

[11] Demand response can be quantified with empirical estimates of elasticity to electricity prices. Typically these elasticities are classified in long-term, short-term and elasticities to time-of-use tariffs. Only a few studies investigate real-time elasticity. Patrick and Wolack (1997) estimated real-time elasticities for five industry

charging events. This is one of the reasons that more than 20 dynamic pricing studies with over 100 pricing designs took place in North America, Europe, Australia and New Zealand over the past decade (Faruqui and Palmer, 2011). The reduction in peak demand for these studies varies from 0% to 60% and enabling technologies like smart meters or in-home-display systems are likely to produce better results. Moreover, designs where the pricing ratio between peak and off-peak hours is higher tend to have a greater impact on peak reduction. In particular, Faruqui and Palmer (2011) showed that there is a logarithmic relationship between this ratio and the reduction in peak demand

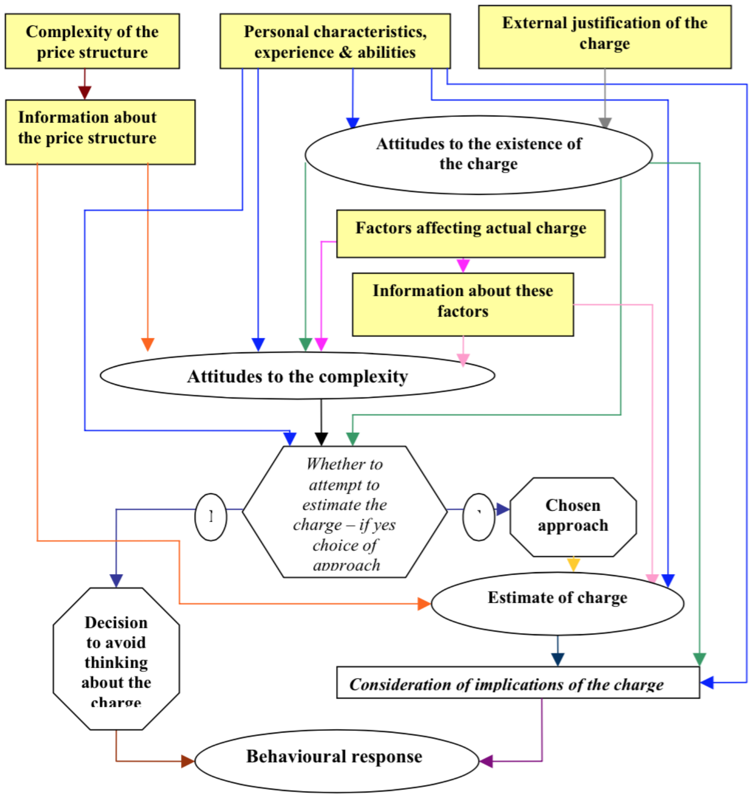


Figure 2.3: Heuristic for response to complex price signals. Reproduced from (Bonsall and Shires, 2005)

Several utility companies in the U.S. have introduced EV-specific Time-Of-Use (TOU) tariffs in order to incentivise off-peak charging behaviour. Faruqui et al. (2011) examine the demand response specifically for EV charging and estimate that even for highly differentiated TOU tariffs, the monthly savings for the drivers would be lower than $50.

sectors in the UK, concluding that substitution in electricity usage patterns mainly comes from substitution across adjacent hour slots. Both in this study and in Lijesen (2006) the elasticities are low, possibly due to the fact that only a small percentage of the consumers have access to real-time price information. Lijesen (2006) also provides a detailed literature review of empirical studies in this area.

They also speculate that if the price elasticity of charging demand is not higher than the elasticity estimated for in-home TOU pricing applications (approximately -0.04), it is unlikely that charging regimes will significantly change. Based on simulations, they found that peak time charging would be eliminated with an elasticity of -0.80 and it would be reduced to half with an elasticity of -0.25. Using existing TOU tariffs, Biviji et al. (2014) estimated the own-price elasticity for EV drivers to vary between -0.362 and -4.358 underlining the fact that managing charging events is characterised by a higher degree of flexibility than managing residential use of electricity.

Apart from cost-conscious, EV owners are likely to be socially and environmentally conscious and hence they are likely to conform to variable tariffs anyway. Also, there is a possibility that with the introduction of electronic timers for smart charging, EV drivers will benefit both from lower charging prices and from maintaining their convenience by plugging-in their vehicles as soon as they get home. Faruqui et al. (2011) suggest a methodological approach to collect real-world data in order to understand the response to smart prices for EV charging. Their recommendation is based on a social experiment, including a control group and three treatment groups corresponding to different TOU tariff structures.

Kurani et al. (2014) have conducted personal interviews and focus groups with residents of California that owned or leased an EV, aiming to understand the effect that pricing had on their charging regimes. One important finding of this study was that drivers had different reference prices as comparative values to electricity price (e.g. gasoline price, value of time etc.). Moreover, it is argued that prices carry additional information signals (e.g. high prices are possibly associated with peak demand and hence service disruptions) and individual actions might be driven by the desire to acquire social benefits.

Pilot studies have demonstrated that there is potential to affect peak demand or even to reduce total electricity consumption with the use of dynamic pricing. Nevertheless, there is little evidence on what pricing structures would consumers prefer if they had a choice. Dütschke and Paetz (2013) designed a conjoint experiment to examine these preferences for attributes like the level of automation in demand response (manual or smart appliances), the spread between dynamic tariffs and the level of dynamics (fixed, variable or dynamic tariffs). The results partly support their initial hypothesis that users, in general, prefer high-comfort (i.e. automated response or relatively static prices) and low-spread (i.e. minimal risk) programs.

There has been extensive discussion around the ethics of applying dynamic pricing methods. Some believe that they would not be beneficial to low-income individuals due to the fact that they already consume limited amounts of power and hence they don't have the required flexibility to shift their behaviour. Nevertheless, Faruqui and Palmer (2011) exhibited that even without reacting to price signals, more than half of the low-income residential customers benefit from these schemes because they have a relatively flat demand curve. Another argument that the authors confute is the lack of dynamic pricing experience for electricity customers. Indeed, numerous markets (airlines, theatres, hotels etc.) have been adapting theirs prices to fluctuating demand for decades and, thus, people are not unfamiliar with this concept. Besides, the studies mentioned above revealed a significant degree of satisfaction among participants who managed to save money by responding appropriately to dynamic pricing.

2.3.10 Demand for Vehicle-to-Grid

EVs offer a great opportunity for electricity storage through the interaction of the vehicle with the grid under an operator's control, widely known as Vehicle-to-Grid. Considering that cars remain parked for the greatest part of the day (approximately 95% of the day for the UK) (Huang and Infield, 2009), this idle period can be used for the exploitation of EVs' storage properties especially in solar and wind peak intervals ("*valley filling*"). On the other hand, EVs will feed the energy back to the system when electricity demand is high and it can't be easily matched by generation ("*peak shaving*"). Moreover, V2G is suitable for smoothing fluctuations in electricity generation (*regulation*) and for reserving power in case of unexpected outages (*spinning reserves*).

Here we discuss the implications of V2G for the consumer. One of the main questions is how willing the drivers are to sell power back to the grid and at what price. The benefits of V2G implementation for the power network and several optimisation techniques that have been employed in the literature are analysed in Chapter 5.

Regulation and spinning reserves, otherwise known as ancillary services (A/S), have the highest economic value for V2G markets. The most important property of these services is power availability at any point in time, and as a result, their delivery is paid primarily in terms of capacity (kW) rather than in terms of realised energy transfers (kWh) (Parsons et al., 2014). The idea, thus, is that electric vehicle owners will be compensated for the time they remain plugged-in irrespective of when they feed energy back to the grid. Their relationship with the operators that manage the EV fleets could be either contractual or non-contractual. In the first case, EV owners have the obligation to remain parked for the contracted amount of time per day or per month. Of course, contracts could have relaxations for days with tight driving schedules, as long as other conditions are met. In the second case, there is not such an obligation and owners can get paid according to the amount of capacity they provide. Nevertheless, the non-contractual relationship contains a higher level of uncertainty for the operator.

V2G applications could increase the ability of electricity suppliers to affect travel behaviour of EV drivers. Choices associated with parking, activity durations or even modes of travel could be possibly altered compared to how they are shaped for conventional vehicles.

The battery-related costs that come with the V2G service due to losses in charging or discharging and to the degradation that is caused by the additional cycles can be troublesome for the EV owner. However, according to Kempton and Letendre (1997), V2G still remains a cost-effective solution. The overall vehicle ownership cost could be decreased from getting paid to provide reserve services to the power grid (Kempton and Tomic, 2005a).

Some of the decisive parameters for individuals to get involved with V2G services are:

- The type of contract that they can arrange with the operator
- The SOC and the location of the vehicle
- The remaining travel needs and the required energy

In their choice experiment, Parsons et al. (2014), simulate V2G contracts with varying characteristics, like minimum driving range guaranteed to the drivers after their dwelling period or minimum prerequisite plug-in period. From these hypothetical contract designs, they were able to estimate the willingness of the drivers to sign the contracts based on the payments or cash back they would receive. The authors doubt the effectiveness of fixed contracts with annual cash backs and their benefits to the power market since respondents demonstrated an increased sensitivity to V2G restrictions. This sensitivity could be attributed to the reduced flexibility in car use, the subjective estimation of the duration that the car remains parked, or to their uncertainty about the terms of the contract. Hence, they argue that non-contractual relationships or hybrid payment structures would have a higher potential to appeal to EV drivers and to stimulate the V2G market.

2.3.11 Modelling approaches

EV mobility patterns can be analysed with activity-based approaches incorporating the dynamics of travel demand. Activity-based analysis examines travel behaviour through daily or multi-day patterns that are shaped by personal lifestyles and activity participation (Jones et al. 1990). This approach is ideal for modelling the use of electric vehicles because it allows the evaluation of the aggregate effect of individual travel and charging choices without the need for charging strategy assumptions.

Disaggregation of trips and activities allows the spatiotemporal evaluation of emissions performance and the identification of peaks in the power load distribution. For example, Kang and Recker (2009) construct person-based activity chains from a travel diary in California, including only chains that are vehicle-based with a vehicle that could be substituted by a PHEV (i.e. excluding motorcycles and bicycles). Likewise, Knapen et al. (2012) generate activity-based schedules with the Feathers model to investigate the effect of various individual charging scenarios on the aggregate power demand. In these studies, the generation of activity schedules is only based on travel patterns and it's independent of charging behaviour, thus, not allowing the investigation of DSM strategies like dynamic pricing.

In the transportation modelling literature, there are also trip-based approaches, when the unit of analysis is a single trip instead of a daily trip-chain. Huang et al. (2012) adopt a trip-based modelling approach in order to calculate the economic costs for the households of EV owners and to investigate potential locations for public charging infrastructure. To implement this sort of analysis in the EV modelling area, there is a need to synthesise a daily structure based on distributions of travel times, distances and activity starting-times. For this reason, it can be argued that it is less accurate and hence less suitable than the activity-based approach.

On the other hand, Waraich et al. (2013) have developed an agent-based microsimulation framework that can track the activities that individuals perform throughout the day and assign utilities to them, thus, giving a dynamic character to the energy consumption and the charging duration of the EVs. One limitation of this study, compared to the present thesis, is that the parameters of the utility function are not estimated, but approximated according to exogenous factors (e.g. the current price of gasoline). This framework is built in MATSim (MATSim-T, 2008) and it is based on co-evolutionary algorithms to maximise the utility of individual EV drivers by re-planning their daily schedules and modifying their charging behaviour.

Zoepf et al. (2013) also estimated a charging choice model at the individual level where the variable of interest was the occurrence of a charging event at the end of a journey. The data used for this study came from a Toyota Prius trial that took place in the United States between 2011 and 2012. Although their mixed logit specification has the potential to predict future charging behaviour, the limited variability of electricity tariffs does not allow the estimation of charging cost sensitivity, which is one of the main contributions of the present study.

The combination of this bottom-up treatment of charging demand with a top-down approach of the network operator gives the opportunity to assess the aggregate impact of the multiple individual charging events at a system level (Acha et al., 2012). The main advantage of employing agent-based techniques to model charging behaviour is that the high granularity of the road network can be effectively mapped to the power grid system, allowing in a way the simultaneous analysis of the two network systems. Moreover, they are ideal for policy analysis by implementing different control methods (e.g. differential pricing) and examine the results on travel and charging choices (e.g. departure time, driving mode for PHEVs etc.).

Most of the studies mentioned in this chapter use exogenous car-driving patterns to represent EV daily schedules and they apply charging scenarios similar to the ones listed in subsection 2.3.7 to simulate the charging choices of the drivers. With a few exceptions (Waraich, 2013; Dong and Lin, 2012; Zoepf et al., 2013) these models are not sensitive to policy changes because they do not explicitly capture consumer attitudes towards charging.

Moreover, in their majority, they examine only the case of PHEVs and not BEVs. There is no doubt that it is easier to make this assumption that the exogenous patterns are similar for PHEVs due to their capability to keep running when the battery is over. Nevertheless, as it was shown earlier, BEV range is also adequate to cover mobility needs without affecting daily behaviour. What happens though when time-of-day tariffs are introduced that have a significant variance to induce a shift in charging times? Are these assumptions still legitimate when we consider future energy costs, driver preferences and infrastructure availability?

Daina (2014) was the first to explicitly model charging behaviour within a discrete choice modelling framework. In this study, which is based on hypothetical choice situations, the respondents have to make a joint choice of the final battery level that they require for their vehicle together with the preferred timing to achieve this SOC. The choice space, in which the respondents are flexible to "move", is defined by the duration of the charging opportunity, the target battery level for the vehicle and the maximum charging speed that is provided by the operator. This model is restricted to home charging events. The interrelationship of charging timing and activity-travel timing is captured by the following utility function:

$$\begin{aligned} U = \beta_0 + \beta_{SD}(t_1 - t_1{}^*) + \beta_{PV}(T_D - T_D{}^*) + \beta_{TTOUT} TT_{OUT}(t_1) \\ + \beta_{TTIN} TT_{IN}(t_1, T_D) + \beta_{CHT} CHT + \beta_{tSOC} tSOC \\ + \beta_{COST}[TC_{OUT}(t_1) + TC_{IN}(t_1, T_D) \\ + CHC(t_0, SOC_0, CHT, tSOC)] \end{aligned} \tag{2.1}$$

where U is the utility of the driver, $t_1 - t_1{}^*$ and $T_D - T_D{}^*$ are the penalties in the departure time from home and in the duration of the activity at the main destination of the tour compared with the baseline, i.e., the preferred times as they are observed in the data, TT_{OUT} and TT_{IN} are the travel times for the outbound and the inbound legs of the tour, CHT is the duration of the charging opportunity, tSOC is the target battery level TC_{OUT} and TC_{IN} are the non-fuel related costs of the tour legs, CHC is the cost of charging operation, t_0 is the time the vehicle is parked at home and SOC_0 is the initial state of charge. Indicative results from this model showed that there is a variation in the valuation of charging duration based on travel purpose. For example, respondents are likely to prefer shorter charging events before a shopping or leisure trip. Moreover, driving distance after recharging is positively associated with target SOC suggesting an underlying range anxiety effect.

2.4 Data collection methods

The major obstacle to modelling charging behaviour is the insufficiency of real-world data because of the limited amount of electric vehicles in the transport network. Revealed charging data could be used to calibrate policy-sensitive discrete choice models of charging behaviour. Detecting the existing few drivers and convincing them to participate in surveys or even to be monitored for some months is a rather inefficient and challenging approach. Consequently, collective actions and partnerships between various stakeholders (car manufacturers, power utilities, universities etc.) are required in order to design EV trials and find volunteers to take part in them.

Electric vehicle trials around the world are essential in order to generate datasets not only on charging behaviour but on battery and component performance as well. Sensing and communication technology developments like GPS devices create new opportunities to collect sophisticated spatiotemporal travel information. Participant privacy and data ownership issues, in general, slow down the research progress of the electro-mobility area but significant steps have been made during the last few years. Representative data that can be collected with these trials are:

- Power flows across the battery terminals
- SOC
- EV position from GPS
- Ignition position
- Brake pedal state
- Ambient temperature
- Ancillary load state

A notable example is the EV Project in the U.S. with 18 cities participating, and a target to enrol 8,300 vehicles (LEAFS and Volts) and install 14,000 Level 2 and DC fast-charging units (combined residential and commercial) (Smart and Schey, 2012). Participants had a charging unit installed at their home for free, in exchange for data collection both from their vehicles and the charging unit. Also, the project was crucial for the deployment of public infrastructure in strategic locations, following an instalment plan that would be beneficial for the users, the owner and the community as a whole.

Another demonstration project, dedicated only to PHEVs, was launched from the Idaho National Laboratory (INL) through the U.S. department of Energy's Advanced Vehicle Testing Activity (AVTA) (Smart et al. 2010). The trial took place in 26 U.S. states, 3 Canadian provinces and Finland and data was collected from onboard loggers in 290 Ford Escape Hybrids and Toyota Prius that were converted to PHEVs. The sample was divided in two (one for commercial use and one for personal use) and all charging events were carried out with a Level 1 rate.

The Ilmenau University of technology in Berlin monitored the charging events of 50 BMW MINI-E's for one year and observed that some of the drivers were not charging their vehicles every day (Westerman et al., 2010). This behaviour is either in line with the "not-every-day" charging scenario described in subsection 2.3.7, or it can be attributed to the fact that those drivers were not using their vehicle every day. Similar MINI-E trials were carried out by the BMW Group in other countries around the world (450 vehicles in New York and Los Angeles and 40 vehicles in the United Kingdom). The UK trial reached similar conclusions for the frequency of charging and provided evidence that time-of-use pricing can effectively shift charging load peaks (BMWGroup, 2011).

Cenex, the UK's first Centre of Excellence for low carbon and fuel technologies, has cooperated with organisations in the North East of England by providing them with electric smart Fortwo passenger cars to evaluate the integration of these vehicles into fleets and the opportunities of targeting at this direction for early adoption (Carroll, 2010). In order to achieve the successful deployment and management of those fleets, Cenex has established partnerships with several councils in this area. The aim of the trial was to collect both qualitative data (from drivers and fleet managers) and quantitative data from logging devices in the EVs. Trip-related information was collected from the vehicle's CAN (Control Area Network) bus and GPS instruments and it was transmitted to a central server every time the driver was turning off the ignition. The trial lasted for 6 months and the results have shown that there was a positive feedback from fleet managers after their experience with the vehicles and the rating for this experience was even higher for organisations with access to dedicated charging infrastructure.

Switch EV, another EV trial that took part in the North East of England between November 2010 and May 2013, covered equipment and installation costs for various charging point technologies (3,7, 22 and 50KW outlets) in public and workplace facilities with the hosts providing free electricity to the drivers as an exchange. Several EV commercial models were used including the Nissan Leaf and the Peugeot iOn. One uncommon characteristic of this trial is the collection and availability of information regarding payment transactions, by monitoring both the vehicle loggers and the charging devices (Hubner et al., 2013). It is also one of the first trials to introduce a membership scheme and the real-time information map with charging post availability.

In Birmingham and Coventry, 108 EVs were monitored for the purposes of the CABLED trial. Half of the participants had smart meters installed at home and they were reimbursed for charging their vehicles off-peak (Robinson et al., 2013). Out-of-home charging stations were also installed, with prices varying from free up to some amount that was levied for parking.

Congested urban areas with great diversity in land use and extended public transport networks, like Central London, are of high interest for testing EV use. The Technology Strategy Board (TSB) has already conducted similar trials in London. Two examples are: a) The Mercedes Smart trial with 60 EVs deployed to residential customers and smart meters installed by EDF to evaluate charging behaviour and users' response to tariff incentives and b) The Toyota Plug-in Hybrid trial with 20 second-generation PHEVs, targeting major business customers like TfL and Sainsbury's (Marantes, 2009).

Last but not least, an EV trial was undertaken as part of Low Carbon London (LCL), a project of UK Power Networks (UKPN). The aim of the LCL was to analyse the impact of various low carbon technologies on London's distribution network. In the trial, there was a mix of residential and commercial participants. Among the 72 residential participants, the 47 were already EV drivers, while the remaining 25 were leased a Nissan Leaf for the purposes of the trial. Apart from the onboard loggers of the EVs, data was collected from Source London infrastructure that was used for recharging. Moreover, socio-economic information and driving patterns were collected from questionnaires that have been designed from the Centre of Transport Studies at Imperial College. Some notable conclusions from the subsequent analysis were that peak demand for residential users occurred around 09:00 pm in the evening and that public charging infrastructure was used mainly as an "insurance" policy and not as part of the drivers' routine (UKPN, 2014).

The characteristics and the key findings of the EV trials described above are summarised in Table 2.3.

A qualitative comparison of the observed charging patterns from EV trials and the charging scenarios presented in 2.3.7 suggests that the existing modelling techniques can capture the aggregate charging load both in the presence and in the absence of differentiated electricity tariffs. Nevertheless, without a disaggregate analysis of charging behaviour it is difficult to link the various charging scenarios with the idiosyncratic characteristics of each area, and hence, it is possible to overestimate or underestimate the magnitude of charging demand. The need to capture heterogeneity in charging choices is supported by the work of Franke and Krems (2103c) who showed that the starting point of a charging event is affected by the user-battery interaction context.

Table 2.3: Characteristics and key findings of representative EV trials

EV Trial	Location	Vehicles	Charging infrastructure	References	Key findings
EV Project	18 cities, 6 states, U.S.	Nissan Leaf Chevrolet Volt	Level 2 DC fast-charging	Smart and Schey, 2012	82% of charging events took place at home locations. 70% of vehicles were observed to charge out-of-home. The project was crucial for the deployment of public infrastructure in strategic locations.
AVTA	26 U.S. states, 3 Canadian provinces Finland	Hymotion Prius conversion PHEVs	Level 1 (110V)	Smart et al., 2010	The evening peak from personal-use PHEVs for weekdays was between 04:00 pm and 10:00 pm. The demand for weekends was significantly lower.
Mini E trials	Berlin New York Los Angeles UK	BMW Mini E	Single-phase 35A	Westerman et al., 2010 BMW Group, 2011	Some drivers do not charge their vehicles every day. Time-of-use pricing can effectively shift charging load peaks.
Smart move trial	North East England	Smart Fortwo	13A/ 240V	Carrol, 2010	Positive feedback from fleet managers after their experience with EVs. Experience was even better for organisations with dedicated infrastructure
Switch EV	North East England	Nissan Leaf Peugeot iOn Avid Cue-V Liberty eRange	3kW, 7kW, 22kW and 50kW outlets	Hubner et al., 2013	Charging behaviour is influenced from free out-of-home charging. All drivers were within 15 km of a charger for 99% of driving time.
CABLED	Birmingham and Coventry	Mitsubishi i-MiEV	Same as above, provided by Plugged-in-Places (PiP)	Robinson et al., 2013	77% of journeys lasted less than 20 minutes. Most drivers recharge when it is convenient. The average charging time was between two and three hours.
Low Carbon London	London	Existing drivers and leased Nissan Leaf	1.7kW, 3.7kW, 7.4kW Source London infrastructure	UKPN, 2014	Peak demand for residential customers occurred around 09:00 pm and public charging infrastructure is not used as part of the drivers' routine.
Toyota PHEV trial	London	Toyota Prius PHEV	Same as above	Marantes, 2009	The average charging duration was 72 minutes. The distance driven for 59% of the journeys was between 3.1 and 12.4 miles

Apart from directly monitoring the driving and charging behaviour of EV owners, there is a great value in talking with them by conducting face-to-face interviews. Kurani et al. (2009) explain how they employed this narrative analysis and how hearing personal stories from the drivers contributed to synthesising the general framework and explaining the meanings behind their actions. Although these interviews can be guided based on previously collected personal information (e.g. travel patterns or vehicle design preferences), they have an open-ended character so that a wide range of perspectives is represented and emerging themes are highlighted.

Kurani et al. (2007) examined the early stage experience of PHEV use by interviewing 23 drivers, including also questions regarding their perceptions of drawbacks and benefits as well as their suggestions for future designs. Perceptions and attitudes towards the essential characteristics of the new technology (acceleration, driving style, environmental feel and noise) were analysed for the Smart Move trial (Carroll, 2010) after the completion of a questionnaire by the fleet users. Tal et al. (2014) implemented an innovative approach to collect self-reported travel and charging data, with the use of a web map (Figure 2.4). The major advantage of this method is its cost-efficiency by overriding costly travel diary administration and installation of monitoring equipment. Additionally, the nature of the survey tool allows them to infer the subjective needs of the drivers and their willingness to pay.

Stated preferences (SP) exercises are also very important in order to explicitly model the behaviour of respondents when they are faced with hypothetical situations. In the area of electro-mobility, most of the SP studies are oriented around customer's intentions to purchase electric vehicles rather than their preferences around the everyday use of the vehicle (Hidrue et al., 2011). One common problem with designing such a choice experiment is the lack of knowledge regarding the underlying technology and the complexity in processing several unfamiliar concepts (e.g. range anxiety, combination of driving modes for PHEVs, etc.) in a short period. Drivers have no constructed preferences for these attributes and, therefore, it is difficult for them to foresee how they would use the new technology and why they should buy it.

Moreover, their choices are affected by their current experience with conventional vehicles, and this asymmetry in experience might lead to biased estimation of parameters that have significant differences (e.g. driving range). For this reason, the use of traditional SP methods in electric vehicle preferences has been criticised (Turrentine et al., 1992; Kurani et al., 1996).

Turrentine et al. (1992) tried to assess the adaptability of households to limited vehicle range trough purchase intention and range simulation games (PIREG). In these games, respondents provided their activity-travel diary and then they were asked to adjust it in order to cope with the hypothetical limitations from the use of an electric vehicle. Gaming and Simulation (GS) approaches like this one have the disadvantage of increased complexity and, as a result, it is more difficult to achieve large samples for model estimation.

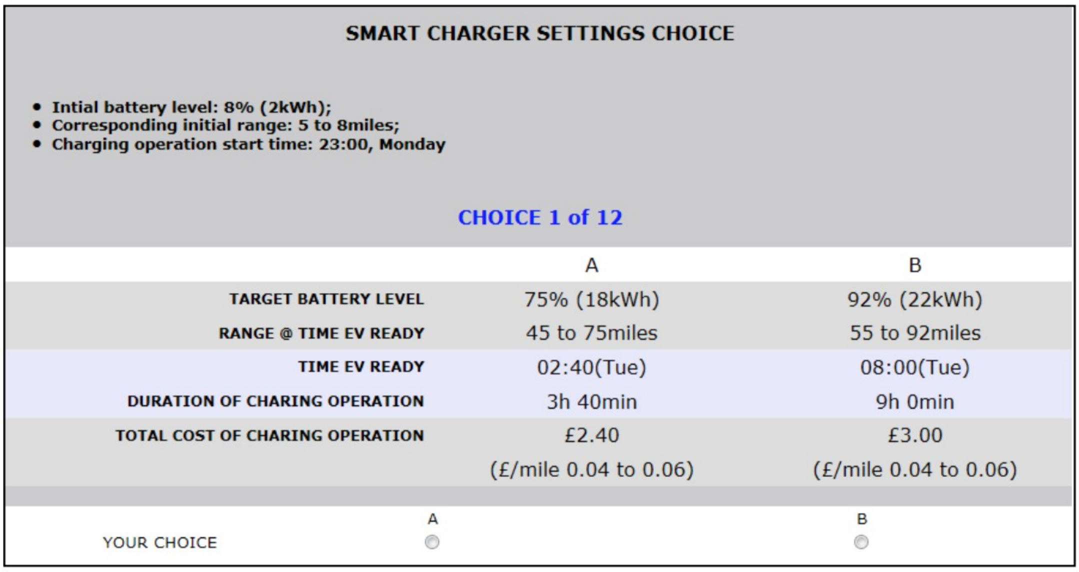
Figure 2.4: Web map for self-reported driving and charging habits. Reproduced from (Tal et al., 2014)

Kurani et al. (1996) were the first that attempted to enrich their stated preference instrument with in-depth information for EVs and at the same time to address the sample size problem in what they describe as a “reflexive design”. Along the same line, Axsen and Kurani (2008) used information from a travel diary that they administered to their respondents in order to visualise their recharge potential. Then for the exercise, they provided them with this visual material as well as with details for PHEV upgrade components to help them take a more informed decision. In contrast with typical choice exercises, this was a *design exercise* because instead of a choice set the respondents were able to design their own vehicle of preference out of a design envelope. Their target population was comprised from regular drivers that were likely to buy a new vehicle in the short-term future. Both studies, by using exercises prior to the SP choices intend to mitigate the negative effects from the lack of experience in the valuation of the vehicle attributes.

The combination of SP data with real-world trials has enabled the comparison of user preferences before and after experiencing EVs. Jensen et al. (2014) have developed a panel survey and observed that even though perceptions for driving performance improved after the trial, the drivers were more concerned regarding their ability to maintain their mobility level.

Parsons et al. (2014) investigated the preferences of 3029 randomly selected respondents in the U.S. regarding V2G-enabled electric vehicles. The complexity of their choice experiment is even higher than for the ones described earlier because not only there is the need to make choices for an unfamiliar topic (i.e. electric vehicles), but these choices are combined with a completely new and obscure element, this of selling power back to the grid. Their strategy to overcome this complexity was to follow a sequential, two-step choice process. Respondents had first to decide between conventional gasoline and typical electric vehicles, and only when they have raised awareness of the attributes of the new technology, were they introduced to the concept of V2G contracts. The comprehension of this methodological approach was supported by conducted focus groups. Another interesting aspect of this study is the treatment of the "yea-saying" effect (i.e. the tendency to overestimate the EV choice because some respondents present a more environmental-friendly aspect of themselves), which might have a significant impact in several adoption studies.

In the area of charging behaviour, the only SP survey known to the authors is this of Daina (2014). Of course, the difficulties are similar with the design of choice experiments for the adoptions of EVs because there is a low degree of familiarity with the hypothetical charging situations presented to the respondents. The author suggests that there are two levels of imagination that the respondents have to go through when they are making their charging choices: the process of using an electric vehicle itself and the fact that recharging their car might demand more planning than just plugging it in. For this reason, they are first presented with a stated adaptation section where they are allowed to configure the charging settings and observe the effects this could have on their daily activity schedule. Then they complete the SP exercise, by choosing between different charging attributes (i.e. final SOC, driving range after charging, duration and cost of charging operation) for a given initial SOC and a starting charging point tailored to the individual's completed travel diary. A typical choice card from this survey looks like the one in Figure 2.5.



SMART CHARGER SETTINGS CHOICE

- **Intial battery level: 8% (2kWh);**
- **Corresponding initial range: 5 to 8miles;**
- **Charging operation start time: 23:00, Monday**

CHOICE 1 of 12

	A	B
TARGET BATTERY LEVEL	75% (18kWh)	92% (22kWh)
RANGE @ TIME EV READY	45 to 75miles	55 to 92miles
TIME EV READY	02:40(Tue)	08:00(Tue)
DURATION OF CHARING OPERATION	3h 40min	9h 0min
TOTAL COST OF CHARING OPERATION	£2.40 (£/mile 0.04 to 0.06)	£3.00 (£/mile 0.04 to 0.06)
YOUR CHOICE	A	B

Figure 2.5: Example of hypothetical charging choice scenario. Reproduced from (Daina, 2014)

2.5 Summary

During the last decade, a great variety of electric vehicle technologies emerged in the automotive market (e.g. BEVs, PHEVs, E-REVs etc.). Among these technologies, PHEVs seem as the most promising alternative to conventional ICEs, at least for the initial stage that drivers will hesitate to rely on pure BEVs. The capability of PHEVs to switch their operation mode from electricity to gasoline when the battery is running low can reduce the effect of "range anxiety", one of the main psychological obstacles in the adoption of electric vehicles. As it was described in section 2.2, the limited range is only one of the numerous parameters that might affect the decision of an individual to purchase an EV.

Several choice modelling frameworks were developed in order to understand the main motives of the drivers and to predict the future sales of EVs. Nevertheless, little attention was given to the choices that take place during the actual use of these vehicles. The prolonged duration of charging events, the uncertainty about future electricity prices or the difficulty in processing complex price signals, as well as the lack of information for public infrastructure availability are some of the problems that an EV driver could encounter on an everyday basis. Therefore, modelling and understanding of charging behaviour is necessary not only to ensure the proliferation of the new technology but also to design new charging services that will facilitate the use of EVs and turn them into a competitive alternative to conventional vehicles.

The frequency and location of charging events are probably the most prominent characteristics of charging behaviour. Revealed preferences from real world trials differ in this aspect, according to the area of study and the distinctive attributes of each trial (e.g. recharge potential at home, tariff programmes etc.). In modelling studies, it is usually assumed that charging is directly proportional to parking opportunities, and hence travel data are analysed to estimate the dwelling periods for the individuals.

Moreover, there is a lot of variability in modelling the required energy levels and the SOC that triggers the initiation of a charging event. For simulations, it is typical assumed that individuals start their day with a fully charged battery and hence it is required to reach the 100% SOC overnight. Stochastic methods have been implemented to capture the uncertainty in the time elapsed between two consecutive charging events. The "safety" battery level that drivers would prefer to have available has been also examined from a psychological perspective, highlighting the multidimensionality of the problem. For this reason, attitudinal questions were included in the online survey (Chapter 3) in order to identify the effect of unobserved factors on charging behaviour.

The amount of electricity that is required for a charging event is also a function of driving distance, driving style (e.g. aggressiveness, acceleration etc.), technical characteristics of the charger and vehicle type. Both disaggregate and aggregate modelling of EV recharging effects, strongly depend on the assumptions made for the factors above. Different approaches have been presented, but a more comprehensive summary can be found in Appendix C.

As it will be explained later, the level of complexity of the designed SP survey did not allow the estimation of users' sensitivity to V2G-related attributes. Nevertheless, considering the analysis for V2G scenarios that is undertaken in Chapter 6, it was necessary to make the appropriate assumptions for the associated demand. The work in this area is still in a premature stage, yet, some guidelines for the relationship types between customers and operators (i.e. contractual and non-contractual) and the respective benefits for the former were discussed.

Out-of-home charging choices are strongly interrelated with the choices for parking (type and location) and this is an area where gaps have been identified in the existing literature. Future parking policies have to be adapted to the increasing deployment of charging infrastructure. For example, charging employees for plugging-in their vehicles at workplaces is not a straightforward task and further research is required. Nicholas and Tal (2013) argue that low charging rates (i.e. 1.2kW) are sufficient for 50%-80% of charging needs at the workplace and that higher rates should be more expensive than electricity at home.

The main attributes that affect parking choices have been analysed so that they can be properly integrated with the joint charging/parking choice-modelling framework of this thesis. Finally, the advantages of applying reservation systems in the parking industry were discussed, since this is a vital component of the suggested revenue management model.

In terms of pricing, charging in private facilities entails a combination of parking costs and electricity costs. The latter might fluctuate based on spatiotemporal energy demands and the importance of DSM strategies in order to avoid peak loads is highlighted. Furthermore, it is attempted to identify the users' response to these strategies, based on the experience gained from their application in household energy consumption. Empirical evidence shows that individuals are more likely to respond when the price signals are not complex enough to discourage them.

As a result, charging services in the following chapters are depicted as "bundles" of parking spaces and energy quantities, in a way that their trade-offs are more transparent compared to the typical smart charging approaches. This bundling is an expression of second-degree price discrimination or nonlinear pricing where the prices do not vary across customers, but according to specific quantity or quality traits of the service.

The final and most crucial part of modelling charging behaviour is to understand how drivers will combine all the information above to take their final decision. In their majority, researchers assume pre-defined charging strategies (e.g. dumb charging or off-peak charging) and they evaluate different scenarios. Since it is rather simplistic to assume that all drivers will behave in the same way, the authors stress the significance of capturing heterogeneity in charging choices with the use of discrete choice methods. This need was also addressed by Daina (2014), however, in this thesis, the focus is towards out-of-home charging events and their joint modelling with parking behaviour.

Before proceeding with the data collection methods in the following chapter, a series of EV trials that have taken place around the world has been presented. The main reason that the revealed preferences from these trials are not suitable for our analysis is the lack of variability in electricity prices (apart from a few studies with dual tariffs) that makes impossible the estimation of response to DSM strategies. Another problem that is emphasised in previous SP studies for electric vehicles is the high level of imagination that is required for someone, especially if he has no experience with an EV, to empathise with the hypothetical charging situations. For this reason, as it will be shown in the next chapter, particular attention was given in increasing the presentational realism of the survey tool, while at the same time the design was aiming to mimic other online services that would be more familiar for the respondents.

3 THE EV-PLACE SURVEY

3.1 Overview

The modelling framework for analysing joint parking and charging behaviour and the associated utility function are presented in the next chapter. However, the marginal utilities for the attributes that influence out-of-home charging choices cannot be estimated with the existing datasets. The ideal dataset for this thesis would enable the exploration of trade-offs between charging and parking attributes, as well as trade-offs between dynamically varying prices for charging services. As a result, this chapter describes the development of an online survey tool that would generate such a dataset. This tool, the EV-PLACE (PLug And ChargE) survey, contains stated preference (SP) experiments that will be used to examine the trade-offs between charging duration, cost, scheduling delays and walking distance from charging place to activity destination and at the same time the response to dynamic pricing in electro-mobility.

The absence of revealed preferences for EVs and especially for tactical decisions, like everyday driving and charging, dictates the collection of SP data through the design and administration of choice experiments. However, even when RP data on EVs is available and accessible to the researchers, the variability of electricity prices is not adequate to estimate the parameters of interest. Ideally, joint estimation of RP and SP electric vehicle data would mitigate the drawbacks of the latter (e.g. hypothetical instead of actual choices). This has not been applied for the present dissertation, therefore, it is suggested for future research.

The capability of SP experiments to replicate real-market decisions (Carson et al. 1994) is one of the main reasons that they have become the predominant method of collecting data for behavioural analysis across diverse choice contexts. Usually in SP experiments, respondents are presented with a series of choice sets that consist of several alternatives, which in turn are defined by a set of attributes and the combination of their levels. After comparing the attribute levels, they have to select their preferred alternative for each choice set.

There are advantages and disadvantages in using SP methods instead of RP ones. Some of the main advantages are:

- In RP data, there is typically invariance in attribute levels. SP experiments provide the opportunity to introduce this variance.
- Attributes in RP data are usually correlated. The proper statistical design of SP experiments can minimise such a correlation.
- RP methods can be used only for alternatives that exist in the market. On the other hand, SP methods can be used to evaluate the preferences for non-existing products or services.

The flexibility expressed in the previous points is quite beneficial for retrieving sensitivities to distinct attributes (Louviere et al., 2000).

On the other hand, the reliability of SP data depends on the level of faith that the researcher puts on respondents actually doing what they have stated, when faced with a real choice situation.

One aspect of SP experiments that has not received so far much attention in the literature is the discrepancy between the setting in which a choice is made in the real world and the setting in which it is made during the experiment. Typically, the attributes of the alternatives are listed in a table for cross-comparisons, which does not resemble the majority of real world travel decisions (e.g. mode choice or route choice) apart from some exemptions (e.g. vehicle choice through car magazines or online channels).

The development of online shopping has created an artificial choice environment, which, by nature, has higher resemblance with the presentation of SP experiments (Collins et al. 2012). Some of the travel choices that can be facilitated with the use of Internet or affected by online information are: renting a car, buying air tickets, selecting a route with the assistance of map tools and combining public transport modes based on personalised information. As a result, there is a great opportunity to amend the presentation of SP scenarios related to these choices, in order to make them look more like the online applications used for real world decisions. Collins et al. (2012), after comparing the results from an interactive survey that was designed like an air-ticket booking engine with a traditionally designed SP, have shown that the former led to better parameter estimates and lower variances in the random part of the utility.

One significant novelty of this thesis is the development of a survey, which mimics the environment of a hypothetical online/smartphone application that could be used to book a charging place for an EV in advance. The ReadyToCharge project (Ioakimidis et al., 2013), which has been developed as a service of a larger project by the University of Deusto on Smart Grids (UDSmartGrid) in Spain, provides an example of the interface and the specifications that such an application could have. This method results in the improvement of presentational realism, which is particularly useful in the charging context. The reason is that EV drivers have a certain level of familiarity with online reservation systems while the same is not necessary for out-of-home charging situations.

The originality of the developed survey tool lays in the fact that it is the first time that parking choice is assessed under the consideration of EV charging characteristics. Moreover, contrary to the majority of EV studies, it does not focus on a strategic choice of vehicle purchase but on a series of tactical choices for the every-day use and charging of an EV. Daina (2014) has also addressed this rather dynamic choice process in the context of charging in a smart grid environment. However, the survey administered for this study combines two innovative elements: out-of-home charging preferences and response to dynamic pricing.

The structure of Chapter 3 is the following:

- Section 3.2 provides the outline of the EV-PLACE survey and the two SP experiments that it entails.
- Section 3.3 presents the statistical design of the two SP experiments: the charging game and the booking game.
- Section 3.4 describes the insights gained from the piloting stage of the EV-PLACE survey, including a focus group that has been conducted, and the conclusions that have been reached for the final design of the survey tool. Both the pilot and the focus group were very helpful in refining the survey and designing the final version, as it is presented in sections 3.2 and 3.3.
- Section 3.5 explains why the online administration method has been selected and describes the recruiting process that has been followed to obtain the full-scale sample.
- Section 3.6 presents the characteristics of the final sample and a basic descriptive analysis of the responses.

3.2 Outline of the EV-PLACE survey

The EV-PLACE survey is an online administered data collection tool. It consists of six sections as they are presented at the beginning of the survey to the respondents (Figure 3.1).

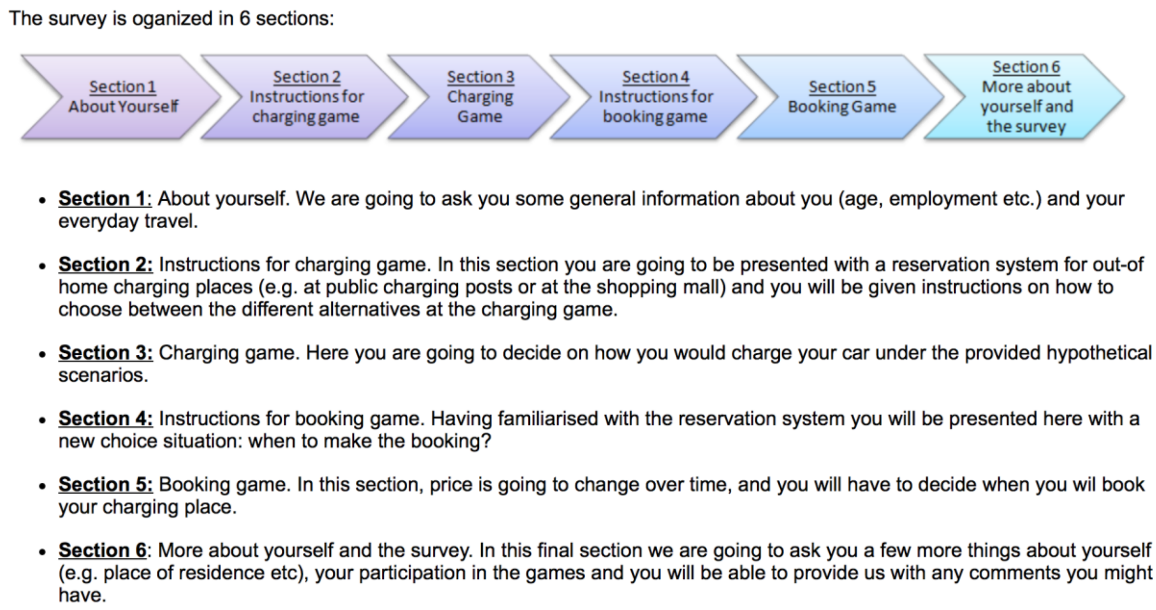


Figure 3.1: Structure of the EV-PLACE survey

The different parts of the survey are described in more detail in the following subsections.

3.2.1 Socio-demographics and travel patterns

In Section 1 of the survey, information is extracted for the socio-demographic characteristics of the respondents such as age, gender, employment status and place of residence. Thereafter, there is a question of whether the respondent owns or leases an electric vehicle in order to reveal an extra part of the survey addressed only to EV drivers[12]. This extra part assembles evidence on their driving and charging habits including questions regarding the frequency of using their vehicle, their typical driving distances and the most frequent charging locations. Last but not least, there is a set of attitudinal indicators that aim to capture charging strategies of the drivers and they are based on the measures that Franke and Krems (2013c) have developed in order to assess the effect of the User-Battery Interaction Style (UBIS) on charging behaviour. Finally, the respondents have the option to provide some

[12] The reasons for recruiting also people without experience of driving an electric vehicle, the criteria for their selection and the sampling strategy are explained later in this chapter

information associated with their energy supplier and if they are subscribed to a differential electricity tariff program (i.e. Economy 7 for the UK[13]).

In order to elicit the preferences of the respondents for charging characteristics like price and duration, they are presented with stated preference exercises later in the survey where they have to select among various charging alternatives based on hypothetical daily scenarios. Rose and Hensher (2006) argue that the capability of SP experiments to replicate real market decisions depends on their degree of realism. This realism relies, in turn, on the resemblance of the hypothetical travel patterns with the respondents' actual travel patterns. For this reason, in the same study, it is suggested that alternatives, attributes and attribute levels of the choice experiment should be aligned with the experiences of the respondents.

The common practice in the travel demand modelling literature is to first collect travel diaries and then tailor the choice scenarios to the observed activity schedules, creating thus highly interactive and individualised survey tools (Polak and Jones, 1994; De Jong et al., 2003). This approach inadvertently leads to a certain methodological issue: taste heterogeneity cannot be disentangled from the heterogeneity induced by the huge variety of travel patterns that the customization generates. Furthermore, for this particular study, non-EV drivers and EV drivers that do not charge their vehicle out-of-home might still be unfamiliar with the scenarios, even if the level of realism is maximised for their travel patterns.

For the above reasons, an intermediate solution between a generic and an individualised choice experiment was adopted. Respondents were classified in 96 socio-demographic categories based on the combination of the following characteristics: gender (male or female), age band (less than 30 years old, 30 to 60 years old and over 60 years old), marital status (living alone or living with partner), having children (yes or no), employment status (employed or unemployed) and location (central London, non-central London, outside London).

Le Vine et al. (2011) used a similar classification to allocate the respondents to *avatars*, i.e. artificial characters that have similar socio-demographics with them. The present survey has

[13] Economy 7 offers cheaper domestic electric prices during a 7-hour off-peak overnight period (usually 11:00 pm to 06:00 am)

been initially designed on the basis of the avatar methodology, but then it was redesigned in a more conventional way due to implications that emerged during the piloting phase[14].

The same classification was performed for a sample of London drivers using data from the London Travel Demand Survey (LTDS), which is a household survey carried out by Transport for London since 2005 (TfL, 2011). LTDS combines a one-day travel diary with personal and household questionnaires, providing thus information on the travel behaviour and daily activities of London residents. Finally, each EV-PLACE respondent was assigned with the daily profile that was observed for a London driver of the same socio-demographic group.

A daily profile here is associated with a trip chain (or tour or journey), which can be expressed as a sequence of trips that starts and ends at home and possibly includes one or more intermediate stops (Ye et al., 2007). Trip chains containing only one intermediate stop (e.g. home-work-home) can be characterised as *simple chains,* whereas, if more than one intermediate stops are involved (e.g. home-work-shopping-home), then they are considered *complex chains*. Moreover, trip chains that contain at least one trip with a work-related purpose are referred to as *work-based chains*. It has been found that trip chain complexity and car mode choice are positively correlated since car availability eases the constraints associated with multiple stops. For future research, it would be interesting to investigate this relationship from the perspective of electric vehicle use and the range restrictions that it entails.

In order to analyse the LTDS data and deduce the most popular profiles, the following steps have been followed:

1. All tours where the car was not the main mode were screened out so that only drivers are included in the final sample.
2. Tours that were not home-based (i.e. starting and finishing at home) or tours that involved an intermediate stop at home, hence giving to a hypothetical EV driver a home charging opportunity, were also screened out.
3. As it was anticipated, there were still 1978 trip chain combinations in the resulting sample and consequently, a lot of different daily profiles. The majority of these profiles, however, had very low incidence rates (sometimes single observations) and

[14] The reasons why the avatar methodology was initially selected and the problems that emerged are discussed in section 3.4.

they were excluded from the analysis. The remaining ones were merged into eight home-based tours, presented here along with their respective proportions:

- Home – Work – Home (52%)
- Home – Shopping or Leisure – Home (31%)
- Home – Work – Shopping or Leisure – Home (3%)
- Home – Work – Work – Home (2%)
- Home – Shopping or Leisure – Shopping or Leisure – Home (6%)
- Home – Drop off family/children – Work – Home (1%)
- Home – Work – Shopping or Leisure – Work – Home (1%)
- Home – Drop off family/children – Work – Pick up family/children – Home (2%)

4. Finally, average driving distances of the inbound and outbound legs, as well as average activity durations, starting and ending times were calculated for the 8 profiles and then used for the scenarios of the stated preference exercises.

The 96 groups were cross-tabulated with the eight daily profiles, giving the likelihood of a London driver undertaking a particular tour based on his socio-demographics. Then, instead of directly assigning a survey respondent to the profile with the highest probability associated with his personal characteristics, they were given the option to select among the profiles, which were presented to them in a likelihood order[15]. In this way, the risk of presenting unrealistic choice situations has been reduced, since the respondent was able to search for more profiles if he felt that none of the presented options could describe one of his latest out-of-home daily schedules (Figure 3.2).

After having selected one of the available profiles, the respondent was asked which day of the week he has undertaken the specific schedule, if he remembered, and if it was representative of his regular travel patterns. Finally, there were some attitudinal questions to capture his perception of flexibility for the underlying activities and his perception of mobility necessity in general.

One assumption made at this point is that the observed travel patterns of London drivers are transferable to all survey respondents, who are distributed across the UK and the Republic of Ireland. However, this assumption is based on empirical evidence from international

[15] The customization at this point, as well as for the SP exercises later, is based on JavaScript code.

comparisons, where it has been demonstrated that travel patterns are in most of the cases independent from the spatial setting (Timmermans et al., 2002; Timmermans et al., 2003).

Before proceeding with the next section and the choice experiment, respondents were introduced to a future scenario that would set the context for the choice situations. In particular, they were informed that charging service providers will soon start pricing out-of-home charging places and it is very likely that they will provide incentives to the drivers so that they plug-in during off-peak periods. This short explanation is intended to familiarise them with TOU electricity tariffs. Also, they are asked to consider a situation where they have the same charging needs as now, but they have restricted capabilities of home charging, in order to accept more easily the forthcoming out-of-home hypothetical options.

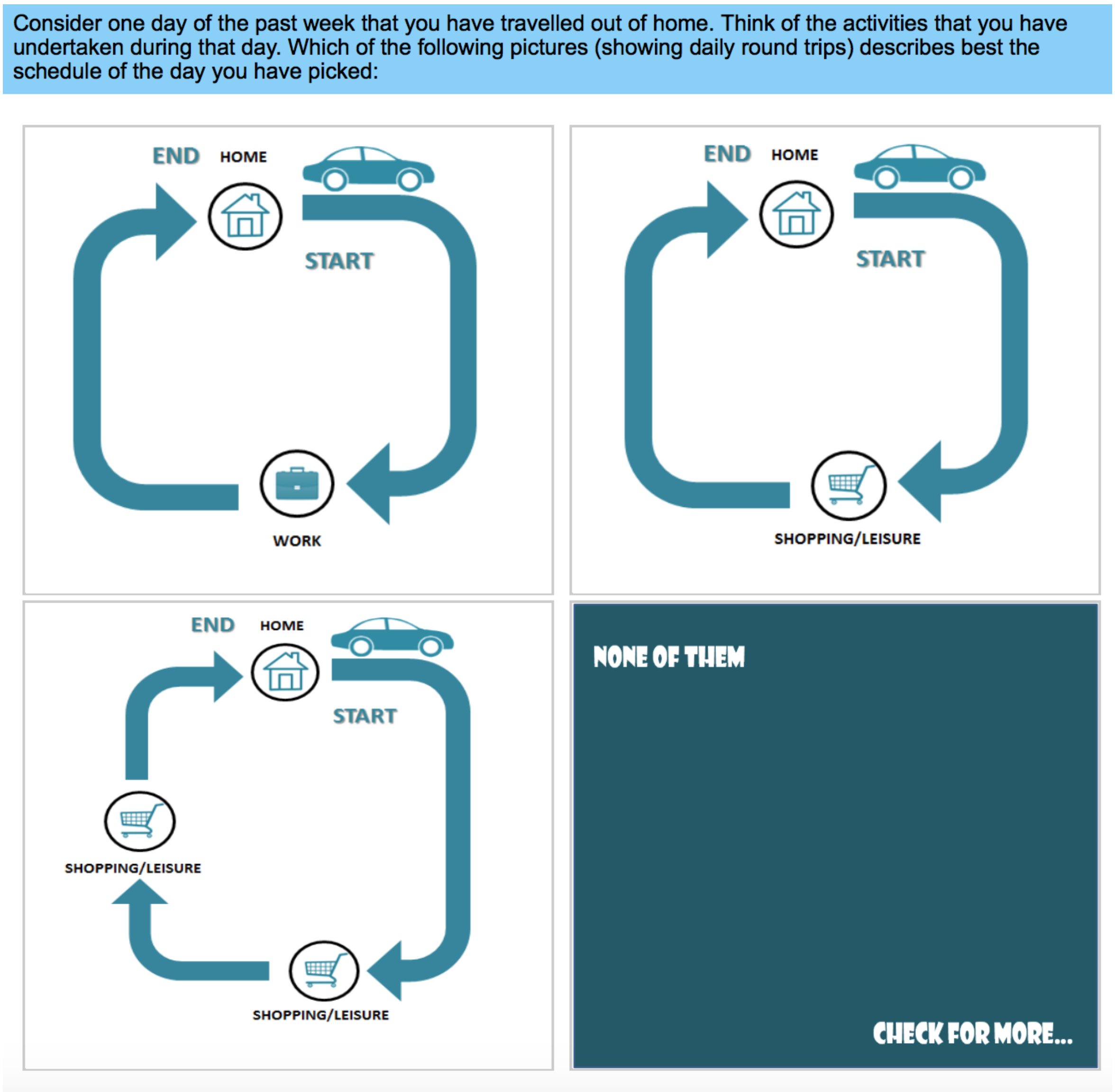


Figure 3.2: Graphic representation of the daily profiles in the EV-PLACE survey

Finally, due to the existence of non-EV drivers into the recruited sample, some important characteristics of electric vehicles like the increased time required for their recharging and their limited driving range is given to those who do not own or lease an EV. In this way, these respondents are familiarised with the terminology of the choice exercises and the constraints that can be imposed by the use of an EV. The same overview is presented to some randomly selected EV drivers so that it is possible to evaluate if there are differences between the two "test groups" and if beliefs for EV technical characteristics are matching their real values.

3.2.2 The Charging Game

In Section 2 of the EV-PLACE survey, the respondents are presented with an instructional video[16] on how to complete the first stated choice exercise, i.e. the charging game. The purpose of this exercise is to elicit individuals' preferences for charging attributes in a hypothetical context where they enter their destination, their activity timings and the required battery level in an online/smartphone application, and a charging service provider offers them alternatives that could accommodate their needs.

In this video, first, they are shown an overview of a choice situation, which is similar to Figure 3.3. Then the various parts of this overview are explained.

The blue box on the bottom-right part of the screen embodies the activity schedule scenario, and it is based on the travel profile that the respondents have selected earlier. Also, it indicates how the battery level of the vehicle changes as the person drives around throughout the day. Obviously, the consumption rate is susceptible to the individual driving style and the technical characteristics of the particular EV. However, the use of approximate mileage, instead of energy units (kWh) or SOC (%), simplifies the comparison of the battery level with the daily schedule and reduces the uncertainty from subjective transformations made by the respondents during the exercise. The possible battery states in each scenario are three:

- Discharging, when the vehicle is driven from one location to another (red arrows).
- Stable, when the vehicle is parked at a location without a charging opportunity (white arrows).
- Charging, when the vehicle is parked at a location with charging post availability (green arrows).

[16] The use of a video as an instructional tool was decided after discussion in the focus group that took place during the piloting stage. The web link for this video is http://evsurvey.weebly.com/video-1.html

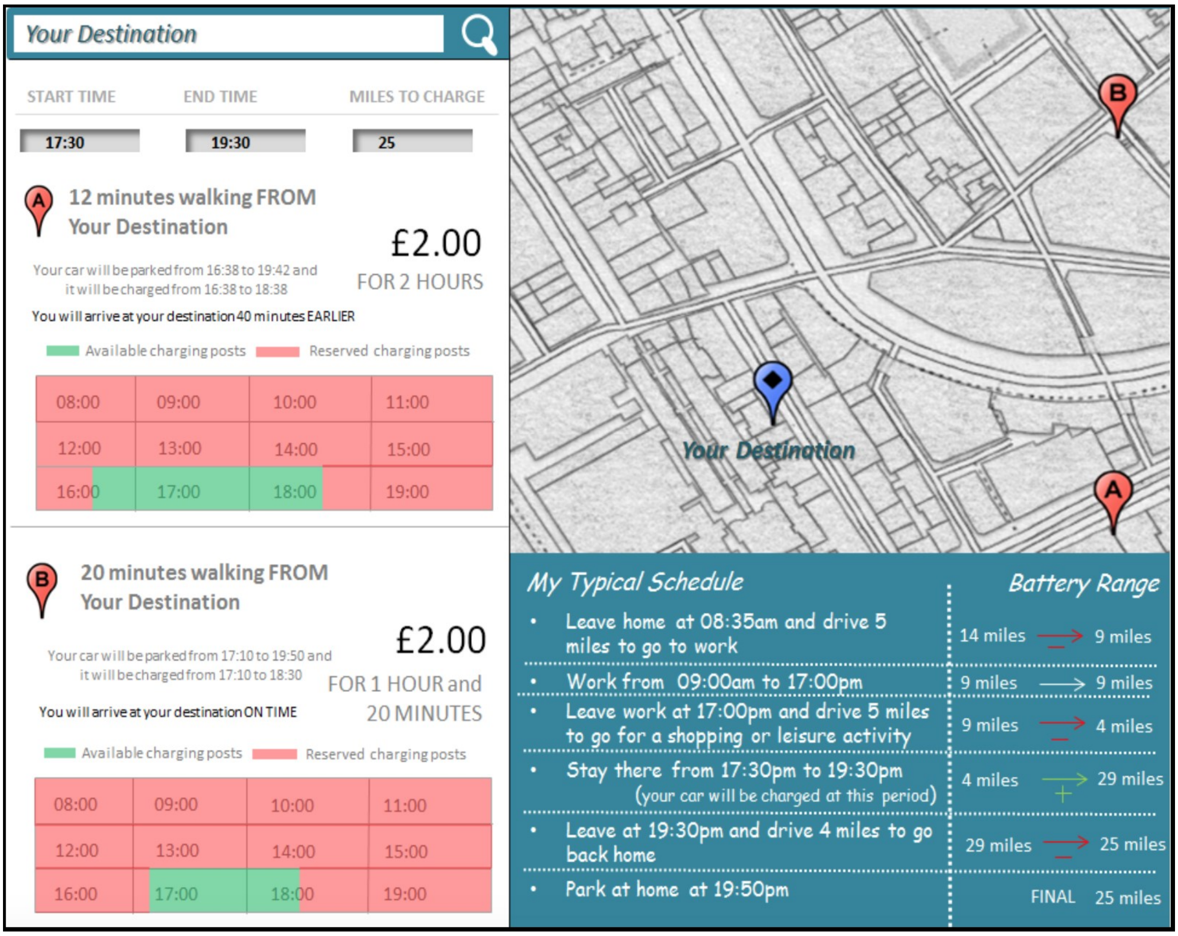


Figure 3.3: Overview of the charging game

Afterwards, the video demonstrates the top-left part of the screen, which imitates the application that the respondent would use to reserve a charging place in advance. The required input here is: the location of the activity with the charging opportunity (e.g. address or postcode), the preferred starting and ending time of this activity and the individual's battery needs for the rest of the daily tour (in miles). For the choice situations, these fields are assumed to be already filled by the respondent, generating thus a list of charging offers from the provider and a map with their locations.

In a real context, this list could contain all the charging places that are available in the proximity of the activity location. For the charging game, it is assumed that only two unlabelled charging alternatives are generated (options A and B in Figure 3.3) and the respondent has to choose amongst them based on four characteristics that are highlighted in the video:

- How far is the charging place from the destination? (e.g. 12 minutes walking),
- What is the price of this charging offer? (e.g. £2.00),

- What is the duration of the charging event? (e.g. 2 hours), and
- Is there a need to arrive earlier at the destination and if yes, how much? (e.g. 40 minutes earlier).

For the last point, further details are given for clarification. The charging service provider, evaluating the reservations that are already made and the occupancy of the charging facility "A", estimated that the only available option for the respondent would be to charge his vehicle between 16:38 pm and 18.38 pm. This period is indicated by the green area of the respective "time-box". The red area indicates time periods where there are no charging places available for the specific facility. Since the driver will plug-in his vehicle at 16:38 pm and will walk 12 minutes to his destination, he will be there at 16:50 pm, i.e. 40 minutes before the preferred starting time for his shopping/leisure activity. Likewise, it can be deduced that by choosing option B, the driver will reach his destination on time.

Before proceeding with the actual exercise, two last points were emphasised. First, the amount of energy to charge is the same for both alternatives (i.e. 25 miles for this example). The reason for charging duration being different for the two options is that they use different charging rates or power levels (in kW). This clarification was essential because some respondents could well assume that longer durations are interrelated with higher energy amounts. Second, there is no need for the driver to return to the charging facility and remove his vehicle once the charging event is over. The vehicle will remain parked until the end of the person's activity and it will always be charged with the required amount at this point. Nevertheless, if the driver decides to leave the charging point before the charging event is over, he will not be provided with the requested SOC but he will still pay the agreed amount.

Hence, it is assumed that the charging service provider applies certain operational methods to reallocate the vehicles within a parking facility after the end of each charging event. These methods could entail employees of the parking facility moving the recharged EVs or parking managers optimising the charging process of adjacent vehicles for charging stations with multiple outlets. Likewise, the charging service provider should be ready to anticipate early departures and to control in real-time the available resources.

The charging game starts in Section 3 of the survey and respondents are presented with nine choice situations based on their travel profile. In all choice situations, they have to select one of the two alternatives and there are no additional options, like mode shift, parking without recharging or activity rescheduling[17]. As it was pointed out earlier, the design variables for this exercise are four: walking time from the destination, price, charging duration and starting time of the charging offer. Some scenario attributes (e.g. driving distance, activity timings etc.) are based on travel profiles, while others (e.g. initial SOC and charging amount) were adjusted for the different profiles based on two constraints: the tour would not be feasible without recharging the vehicle in-between and the charging amount would be deliverable with the existing charging infrastructure[18].

As a result, each respondent was assigned with a profile-specific **initial SOC** that was low enough to make the out-of-home charging event unavoidable, according to the average daily distance that was calculated for the respective profile with LTDS. Since a significant proportion of the survey sample consists of actual EV drivers, there was the possibility to collect information on their typical SOC at the beginning of the day and use this value across the choice situations. This approach was rejected for two main reasons. First, it would require high customization of the design, which is not desirable for the reasons described earlier. Second, in order to create profiles with typical driving distances (in the range of 7 and 18 miles for London drivers), it is essential to use much lower values for the initial SOC than the expected ones so that the tour will be unfeasible without recharging. Therefore, the SOC at the beginning of the tour was considered to lie in the range of 8% -18% of the total battery capacity (EPA, 2013) [19]. The justification for the use of low battery levels in the charging game context is given in Chapter 4.

The **charging amount** was also profile-specific, and it was randomly selected within the small range of 20-30 miles (approximately 25%-35% of the battery capacity or 6kWh-8.5kWh) to represent a typical out-of-home charging event that has mainly the character of a "top-up" for the rest of the daily tour, rather than a fully recharge of the EV. The only constraint for this attribute is the capability to achieve the target quantity within the given time using slow or fast charging stations.

The design variables were all assigned three levels that can be seen in Table 3.1.The levels used for the walking time attribute are based on earlier stated preference studies for parking

[17] The limitations and the reasoning behind this binary choice formulation are explained in the methodological framework in Chapter 4.
[18] Rapid DC chargers are excluded from this analysis.
[19] According to the U.S. Environmental Protection Agency (EPA) a 2013 Nissan Leaf model consumes electricity at 29kWh/100 miles (combined city and highway driving) which for a 24kWh battery capacity gives a range of 83 miles.

choice (Axhausen and Polak, 1991; Golias et al., 2002). However, they are slightly inflated to express the lower availability of charging posts in comparison with on-street or off-street parking places, even for optimistic scenarios of infrastructure deployment.

The charging infrastructure owner has to bear a combination of fixed costs (e.g. parking lot modifications, EV supply equipment) and variable costs. Most likely, the latter consist mainly of the electricity cost, which fluctuates according to the demand, time-of-day, local suppliers etc. On the other hand, revenues for charging facilities are associated both with electricity consumption and with the duration of charging events. Combining the two factors, it can be concluded that revenues depend on the daily distribution of the power (in kW) required for the available charging posts. Pricing per kWh is subject to the sales volume induced by greater distances and pricing per hour is negatively affected by higher charging rates (Williams and de Shazo, 2014).

Table 3.1: Levels of the design variables presented to the respondents for the charging game

Design Variables	Level 1	Level 2	Level 3
Walking time	4 min	12 min	20 min
Price	£1.00	£2.00	£3.00
Charging duration	40 min	1h and 20 min	2h
Starting time of charging offer	On time	20 min earlier	40 min earlier

Differentiating the prices based on the charging rate provides the opportunity to balance the counter effects of the two structures above. As a result, longer and not power-intensive charging options should be cheaper (at their unit price level) than peak-hour, short-interval and highly power-intensive charging options. This tariff structure is demonstrated in the revenue management application in Chapter 6. Nevertheless, for the purposes of the choice experiment, charging duration has been treated independently from charging price, in order to avoid the introduction of correlation between the two attributes.

The range of unit price levels is determined by dividing the lowest price (£1.00) with the highest amount of energy (8.5 kWh) and the highest price (£3.00) with the lowest amount of energy (6 kWh). Therefore, the underlying unit prices across the choice situations are between £0.12/kWh and £0.50/kWh. The average unit cost of domestic electricity for the year 2014 was calculated at £0.1558/kWh (including VAT) based on a consumption of 3,800kWh/year (DECC, 2015). Moreover, TOU tariff regimes like the Economy 7 usually offer unit prices below £0.10/kWh for off-peak periods. The charging cost is amplified here to express the fact that each offer is a bundle of electricity and parking services. Besides, domestic electricity prices are anticipated to rise in the future and there should be an adequate spread between peak and off-peak prices for the successful application of demand-side management methods.

Charging duration levels have been designed in a way that the value of the highest level (i.e. 2 hours) does not exceed the minimum parking duration across the various travel profiles. Finally, the starting time attribute has been designed on the basis of a schedule delay early parameter (Small, 1982). The difference here is that the changes in schedule are not generated by travel time unreliability but from the constraints imposed by the charging service provider.

Several additional parameters, typically encountered in the parking choice literature, have been considered for this SP exercise: parking type (off-street vs on-street), safety, within-facility location etc. However, additional design variables would:

- Increase the complexity of the charging game scenarios for the respondents and jeopardise the reliability of the results. Empirical evidence has shown that the dimensionality of the SP exercise affects the degree at which respondents ignore the presented attributes, not because of the quantity of information, but because of its relevancy (Hensher, 2006).
- Complicate the statistical design of the choice experiment (e.g. additional choice situations, block design etc.)

We believe that the final attributes selected are the most relevant to the decision-making process for the out-of-home charging setting of this dissertation.

3.2.3 The Booking Game

In Section 4 of the survey, respondents are presented with a second instructional video[20]. As before, they are first shown an overview of the new SP exercise, the booking game (Figure 3.4).

The structure of the booking game is quite similar to the previous one. For example, the blue box including the daily schedule scenario and the fluctuations in the battery level is still based on the travel profile of the respondent and has not changed at all. Likewise, the top-

[20] The web link for the second instructional video is http://evsurvey.weebly.com/video-2.html

left part of the screen remains the same, indicating the time and energy preferences of the individual, as well as the location of the activity with the charging opportunity. The additional assumption made at this point is that the respondent has already selected one of the alternatives that were given by the charging service provider (shaded area) and the location of this alternative is indicated on the map.

In the previous exercise, the price of a charging alternative depended on the time-of-day and the location of the charging station, reflecting the effect of the spatiotemporal distribution of EV charging demand on local power networks. This could be defined as the systematic variation of electricity price.

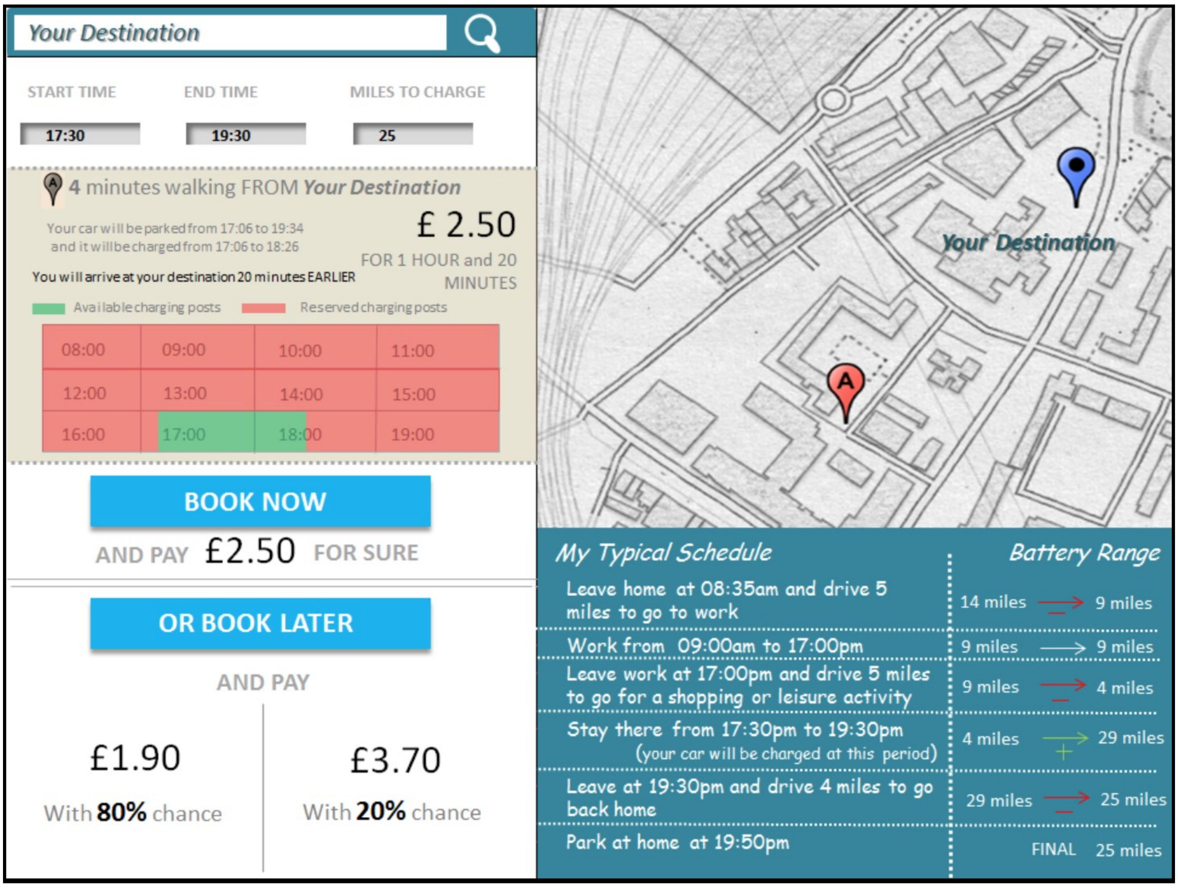


Figure 3.4: Overview of the booking game

If drivers were allowed to make a booking for a charging place earlier in advance, the charging service provider would be able to update his predictions for future demand after each customer arrival. Hence, the application of dynamic pricing in this context would result in different prices for a specific combination of place and time across the booking period. In other words, a driver that wants to charge his car from 10:00 pm to 11:00 pm at parking facility "A", might be confronted with different prices if he makes the reservation the previous day or before he leaves home at the morning. This could be defined as the non-systematic variation of electricity price since it depends on the uncertain evolution of demand throughout the booking period.

The behavioural aspect that is examined with the booking game is the response of EV drivers to the dynamic pricing of charging alternatives. The respondents have to compare the price of their selected charging offer at the moment they enter the online application with an uncertain future price and decide if they should book now or wait to make the booking later.

The cognitive process that takes place, in this case, presents similarities with the decisions that individuals make in other service areas, where dynamic pricing is already applied (e.g. airline tickets, hotels, theatre etc.). Since the respondents should be familiar with some of these areas, they are asked when watching the instructional video to put themselves in a former situation where they had to make an online reservation. Then they are introduced to the notion of dynamic pricing with the following statement: "*Has it ever happened that you delay your purchase only to come back and see that the new price was over your budget? Or have you ever bought a ticket early in advance but next time you visited the website you discovered that the price has dropped? Probably the answer to one, or both of these questions is yes*." This analogy is essential to make a smooth transition from an existing service that can be well conceived by the respondent to the hypothetical application of interest.

Obviously, the mechanisms behind the price changes in these industries are not transparent to the customers. As a result, individuals form subjective probabilities about future prices based on past experiences and their awareness of exogenous conditions (e.g. holiday season). The identification of such subjective probabilities for a non-existing service, like charging places for EVs, is quite challenging and probably unjustified due to the absence of historical data. For this reason, a basic assumption made for the booking game is that the respondents are provided with objective probabilities for future prices from an intermediate agent that has incomplete information about the dynamic pricing mechanisms.

The instructional video contains examples of similar intermediate agents in the airline and hotel industries[21]. After respondents have understood the function of price predictors for

[21] The Kayak airfare website analyses billions of travel queries using algorithms and mathematical models to forecast future prices for airline tickets and to give advice to the users, of whether they should buy or wait for the price to go down. The Suitest, a search engine for hotel rooms, has also a price predictor feature called the "Hotel Time Machine". This feature provides customers with probabilities of future prices and room availabilities, giving also recommendations about the best time to book the deal.

these examples, they are introduced to the hypothetical scenario where there is a price predictor who is providing them with the following information (Figure 3.4):

- The probability of an increased price if they book after a few hours (e.g. 20%), and the respective price (e.g. £3.70).
- The probability of a decreased price if they book after a few hours (e.g. 80%), and the respective price (e.g. £1.90).

The two alternatives for the respondents are either to book now with a guaranteed price, or wait for later, hoping to get a better deal, but at the same time, taking the risk of paying more. The other attributes of the selected charging offer (i.e. duration, walking time and starting time) will be the same, regardless the time of reservation, and they will also remain fixed for all choice situations. The choice process for this game has similarities with gambling and decision-making under risk (e.g. insurances, investments etc.) and, hence, it is treated within a risky-choice modelling framework in Chapter 4.

The quantity of information conveyed to the respondents in each choice situation, as well as the need to convey it appropriately, makes the proper visual presentation of the booking game a complex task, but simultaneously an essential one. In the pilot section (3.4) there is a discussion on presentation styles that have been used in past SP studies to portray uncertainty or variability, the underlying problems and the steps that we have followed to end up with the current style.

The booking game starts in Section 5 of the EV-PLACE survey and respondents are again presented with nine choice situations. As before, they are faced with a binary choice without an opt-out option, which could be to reject the charging offer if they decide to book later and the price increases. This additional option was excluded from the final design because it would generate an ambiguity regarding the final choice of the individual. For example, would the EV driver search for another charging offer or would he decide to leave his vehicle uncharged? And since the battery level is not adequate to cover the daily range needs without charging, what does this "no charging" choice mean: a shift in mode choice, activity rescheduling, or something else? However, by adding the opt-out alternative, this ambiguity would lead to unobserved heterogeneity and hence, it would reduce the reliability of the estimated parameters.

Speaking broadly, the limitation of this binary choice is that the hypothetical setting is not representative of an online reservation environment. For example, if an individual wants to buy an air ticket and the price increases, he has the opportunity to search for a similar flight in a competitive airline company. In this direction, Collins et al. (2012) have developed a survey with the interface and the functionality of an online travel agent, allowing the respondents to search, sort and filter the appearing options. Along with the improved presentation realism, such interactive methods offer the opportunity to examine side actions of the respondent, like the searching process or the attributes that he values most (e.g. price when he sorts the alternatives from the cheapest to the most expensive).

The development of an equivalent tool for EV charging services is a quite challenging task, and since it is not aligned with the main aims and objectives of the present thesis, a static presentation of an online application is selected instead. However, for the reasons mentioned earlier, it could be considered for future research.

Another assumption, that is limiting compared to other price predictors, is that the selected charging offer will always be available if the respondent decides to book later. Nevertheless, parking facilities will have a certain capacity in charging places and there is always the probability that another driver will enter the reservation system in-between and book this particular charging offer. In order to accommodate this scenario, the SP exercise could be extended with an additional attribute: the probability of finding a charging post if the respondent chooses to buy later. This version of the SP experiment has been originally designed, but later it was abandoned since it increased the complexity of the choice task for the respondents in two ways:

- The probability of not finding a charging post should be complemented by its relative "cost". For example, the individual could settle with another charging offer that starts earlier, hence causing schedule disutility. This "cost" would trigger an assessment of the charging characteristics, which has been already examined in the first choice experiment, and not a pure evaluation of the response to dynamic pricing.
- The uncertain dimensions for this scenario are two (price and availability) and the risky choice of booking later is linked with a series of conditional probabilities. The burden of processing this amount of information would be substantial, even for respondents that are familiar with the concept of probability distribution.

For the booking game, the profile-specific scenario attributes (i.e. the initial battery level and the charging amount) have remained the same as for the charging game. The values of the charging characteristics, apart from price, have been randomly selected among the attribute levels of the first SP exercise and were shuffled for the different travel profiles. This intended to introduce variability in charging scenarios and to examine the effect of this variability on the respondents' attitude towards risk.

The design variables are now three and they are all associated with the price of the selected charging alternative. In particular, they are: the probability of an increased price (P_i), the expected increase in price (E_i) and the expected decrease in price (E_d). The probability of a decreased price (P_d) can be inferred by P_i, since $P_i + P_d = 1$. All of them were assigned with three levels, shown in Table 3.2. The base price for the "book now" alternative was fixed at £2.50 for all travel profiles and choice situations and the levels of expected price are evenly spaced from the base.

Table 3.2: Levels of the design variables presented to the respondents for the booking game

Design Variables	Level 1	Level 2	Level 3
Probability of an increase in price (P_i) | *Probability of a decrease in price (1-P_i)*	**20%** | 80%	**50%** | 50%	**80%** | 20%
Expected increase in price (E_i)	+24% (£3.10)	+48% (£3.70)	+72% (£4.30)
Expected decrease in price (E_d)	-24% (£1.90)	-48% (£1.30)	-72% (£0.70)

The range of unit costs for the "booking now" option, based on the different charging amounts, is £0.29/kWh - £0.42/kWh. Likewise, expected future unit costs for the "booking later" option fluctuate between £0.08/kWh and £0.72/kWh. The prices are extended upwards in order to capture periods of simultaneous parking and electricity demand peaks. Furthermore, the magnitude of electricity costs is quite small compared to other ordinary purchases and especially to petrol prices for conventional vehicles. As a result, estimation could lead to insignificant sensitivities to price. A solution to this problem would be to convert daily to monthly expenses. However, response to dynamic pricing reflects a tactical decision-making process while choices on a monthly basis would have a rather strategic character. In order to avoid these implications, it was preferred to adopt high unit costs and a wide spread between peak and off-peak prices.

3.2.4 Debriefing

During the final part of the survey (Section 6), the respondents had to provide some additional personal information (e.g. accommodation type, ethnicity, income etc.), express their level of understanding regarding the two SP exercises and give their feedback for the survey as a whole.

Moreover, they had to respond to a series of Likert-scale questions, aiming to elicit their attitudes and perceptions towards the following aspects:

- Planning in advance
- Range anxiety
- Out-of-home charging
- Parking search strategy
- Adaptation to a dynamic pricing scheme

Finally, similar question types were used to assess how the presented examples influenced their understanding and whether the travel profiles and charging scenarios of the two choice experiments were compatible with their actual daily habits.

3.3 Statistical design

3.3.1 Charging game

The statistical design of the *charging game* is based on an efficient design approach. In general, the objective of designing an efficient choice experiment is to construct choice sets in a way that the estimated parameters from the choice model are generated with as small standard errors as possible. There are several combinations of alternatives that can produce an efficient design. However, the optimal design is this with the maximum efficiency.

Typically, this optimality is achieved when a certain metric related to the asymptotic variance-covariance (AVC) matrix of the estimated parameters is minimised. The AVC matrix is the negative inverse of the expected Fisher Information matrix (Train, 2003), which in turn is equal to the second derivative of the log-likelihood function for the choice model:

$$\Omega_N\left(X,Y,\tilde{\beta}\right) = -[E(I_N(X,Y,\beta)]^{-1} = -[\frac{\partial^2 L_N\left(X,Y,\tilde{\beta}\right)}{\partial\beta\partial\tilde{\beta}}]^{-1} \quad (3.1)$$

where N is the sample size, Ω_N is the AVC matrix, X denotes the attributes of the experimental design, Y denotes the choice outcomes, β is the vector of parameter values that are unknown so prior values $\tilde{\beta}$ (e.g. from pilot studies) are used as best guesses, I_N is the Fisher Information matrix and L_N is the log-likelihood function. The log-likelihood function here depends on the econometric method employed. For the charging game, it was assumed that the underlying choice model is the multinomial logit (MNL).

The most widely adopted optimality criterion in the literature, which is also selected for the design of the charging game, is the D-efficiency, or the minimisation of the D-error (Atkinson and Donev, 1992). The D-error is the determinant of the AVC matrix and it is a single scalar value that can be calculated for many candidate designs. Then, efficient design algorithms can search among the candidate designs and, each time a design with a smaller D-error is found, eliminate the other candidates.

Nevertheless, D-efficiency is not the only optimality criterion encountered in the literature. Instead of using the determinant of the AVC matrix as metric, other possible options are (Kessels et al., 2006):

- A-efficiency, by minimising the A-error (or trace), which is the summation of the diagonal elements of the AVC matrix.
- S-efficiency, by finding the minimum sample size that is required to estimate identifiable parameters within the maximum desired level of variance.
- B-efficiency, by finding designs where the alternatives are "finely balanced" in their systematic utilities.

The D-efficiency of the design depends strongly on the unknown parameter vector since the choice models are non-linear in their parameters. As a result, it is necessary to make *a priori* assumptions for the values of these parameters. The three possible approaches to this problem with their respective optimal design are explained below (Kessels et al., 2006):

- D_0-optimal design: if no information at all is available it is assumed that the *priors* are equal to zero ($\tilde{\beta} = 0$), which implies that respondents have equal preferences for all the presented alternatives.
- D_p-optimal design: if some relatively accurate information is available, non-zero priors $\tilde{\beta}$ are used (Huber and Zwerina, 1996) and empirical evidence has shown that they lead to more efficient designs than the D_0-optimal ones.
- D_b-optimal design: the use of Bayesian design techniques allows the consideration of the uncertainty about the unknown parameters in the design (Sándor and Wedel, 2001) and priors $\tilde{\beta}$ follow a given probability distribution

The associated errors with the above designs are a function of the experimental design X and of the priors $\tilde{\beta}$ so they are equal to:

$$D_0 - error = \det(\Omega_N(X, 0))^{\frac{1}{K}} \tag{3.2}$$

$$D_p - error = \det(\Omega_N(X, \tilde{\beta}))^{\frac{1}{K}} \tag{3.3}$$

$$D_b - error = \int \det\left(\Omega_N(X, \tilde{\beta})\right)^{\frac{1}{K}} \varphi(\tilde{\beta}|\theta) d\tilde{\beta} \tag{3.4}$$

where K is the number of parameters to be estimated, $\varphi(.)$ is the joint probability density function of the random priors $\tilde{\beta}$ and θ are the given parameters of this distribution.

In this dissertation, a Bayesian D_b-optimal design has been adopted because the estimated priors from the pilot were based on a small sample size (19 individuals) of non-EV drivers. Therefore, it cannot be inferred that EV drivers will demonstrate the same sensitivities to charging parameters and there is a certain level of uncertainty around them. Here it was assumed that the priors follow normal probability distributions and the higher uncertainty for specific parameters was reflected in the design with higher standard deviations.

The Bayesian approach requires the evaluation of the D-error over a number of draws taken from the priors' probability distributions. Then D_b-efficiency is calculated as the expected value of the efficiencies for these draws. In order to approximate this expected value, simulation methods are typically employed. Here are some of the simulation procedures encountered in the literature:

- Pseudo-random draws or pseudo Monte Carlo (PMC): points are randomly selected from the probability distribution. This method might be risky for a small number of draws because the calculated expectations depend each time on the particular set of random draws that might cover a specific area of the distribution space.
- Quasi-random Monte Carlo (QMC) (Hess et al., 2005): Better coverage of the probability distribution space, and consequently smaller approximation errors, are achieved with a more systematic, structured and sometimes deterministic approach to sampling from the distribution. Possible variations of QMC methods are:
    - Halton sequences: They are based on the use of prime numbers that deterministically divide the 0-1 space.

- Sobol sequences: They are constructed similarly to Halton sequences, but a different strategy is followed for primes' selection in order to reduce the correlation between one-dimensional sequences.
- Modified Latin Hypercube Sampling (MHLS): One-dimensional sequences of uniformly spaced points of the distribution are randomly shuffled and combined to generate multi-dimensional sequences.

- Gaussian quadrature: Orthogonal polynomials are used to approximate integrals. The main principle of this method is that weights are attached to different draws, and a weighted expected value is calculated. When the priors follow a normal distribution, it takes the specific form of Gauss-Hermite approximation.

In simulation methods, it is important to decide the number of draws to use in order for the Bayesian efficiency to converge to the true level of efficiency, or at least to fall within an acceptable range error around this level. Using too few draws might lead to poor approximations while using too many draws might lead to unreasonably high computation times for the efficient design algorithms to converge. The optimal number of draws to use will possibly depend on several parameters, like the dimensionality of the design, the number of priors, the simulation method and the econometric method employed.

In Bliemer et al. (2008) it was shown that for different model specifications and for priors with standard deviations equal to 0.3 (which is similar to the distributional assumptions made here) the expected error laid within 1%-4% from the true D_b -error with 95 percent probability for approximately 1000 PMC random draws. This deviation was even smaller with the same amount of draws and other simulation methods, like MHLS or Halton sequences. Therefore, it was considered as a reasonable number of draws for the evaluation of alternative efficient designs.

In general, there are two categories of search algorithms that can be used to identify optimal efficient designs: row-based and column-based algorithms. In row-based algorithms, choice situations are selected from a pre-defined set of choice situations (either a full factorial or a fractional factorial design[22]). In column-based algorithms attribute levels are selected over all possible choice situations. Row-based algorithms satisfy better the utility balance criterion and they are more suitable for constrained designs while column-based algorithms

[22] A *full factorial* design contains all possible choice situations, or in other words, all possible combinations of the attribute levels. A *fractional factorial* design is a subset of the full factorial design

satisfy better the attribute level balance criterion and they are more flexible to be applied for larger designs.

RSC (Relabeling, Swapping and Cycling) algorithms are the most widely adopted column-based algorithms (Huber and Zwerina, 1996, Sándor and Wedel, 2001). Starting with an initial design, attribute levels within each column (i.e. across choice situations) could be changed (relabeling). Then, attribute levels could switch places between choice situations (swapping). Finally, attribute levels in each choice situation could be cyclically replaced (e.g. level 1 becomes level 2, level 3 becomes level 3 and so on) (cycling). Since the design for the charging game was created using the Ngene (ChoiceMetrics, 2012) software, the default searching algorithm was implemented, i.e. only swapping as a special case of the RSC algorithm.

An efficient design was selected for the charging game instead of an orthogonal one because information for the parameters was available from the pilot phase, and whenever there is information availability for the priors, efficient designs outperform orthogonal ones. For example, by using efficient choice experiments choice situations with dominant alternatives[23] can be avoided since the criterion of the optimal design is the minimisation of standard errors. Moreover, earlier work (Daina, 2014) has provided good prior knowledge regarding true parameter values in the context of electro-mobility and charging choices.

An experimental design is defined as *orthogonal* when all the parameters are independently estimated and the attribute level balance criterion[24] is satisfied. Essentially, this means that there is no correlation between the attribute levels for each attribute column. For orthogonal coding[25] this translates in the property that the sum of the inner product of any two columns is equal to zero:

$$\sum_{s=1}^{S} x_{j1k1s}\, x_{j2k2s} = 0, \qquad \forall\, (j_1, k_1) \neq (j_2, k_2) \tag{3.5}$$

[23] "Dominant alternatives" situations occur when all the attribute levels of one alternative are clearly preferable than the attribute levels of other alternatives (unbalanced utilities in choice situation) and hence they do not provide any trade-off information

[24] Attribute level balance is obtained when all attribute levels appear equally in the design. This is a desirable property since it provides a good basis for estimation

[25] Attribute levels can be represented with various coding schemes: e.g. design coding (0,1,2,3, etc.) or orthogonal coding ({-1,1} for two levels, {-1,0,1} for three levels, {-3,1,1,3} for four levels etc.)

where s is a choice situation, S is the total number of choice situations, j is an alternative, k is an attribute and x is an element of the orthogonal design X.

In general, efficient designs are not orthogonal. However, a constraint for orthogonality has been added to the swapping algorithm in order to find the most efficient design that is orthogonal at the same time. Obviously, this reduces the efficiency measure of the final design but it enables the generation of unconfounded estimates of the charging parameters due to the imposed statistical independence between the attributes. In particular, the efficient design generated is a sequential orthogonal design (i.e. orthogonality only holds within each alternative) that still allows correlation between the alternatives and not a simultaneous orthogonal design (i.e. orthogonality holds both within each alternative and across alternatives), because the latter would produce a design with a significantly lower efficiency.

The minimum number of choice situations for an efficient design is given by the formula K/(J-1) where K is the number of attributes and J the number of alternatives. For the charging game, this results into 4/(2-1)= 4. Above this value, the more choice situations are used, the more information is gained per respondent and consequently the higher the efficiency of the design. However, when the number of choice situations increases the effort for the respondents increases as well. Given the complexity of this SP exercise, nine choice situations were presented to the respondents, which is considered a reasonable number for choice experiments.

The flexibility and computational speed of Ngene allowed a comparative analysis between the simulation methods that can be applied to find the optimal Bayesian efficient design (Table 3.3). The various simulation methods described earlier were assessed based on their efficiency measures (D_p-error and D_b-error), the statistical significance of the prior estimates and the correlation between the alternatives (mean value of Pearson correlations for each pair). Finally, the efficient design generated with Sobol sequences has been selected, due to its relatively lower D-error and correlation.

3.3.2 Booking game

The experimental design for the booking game does not follow the same procedure as the previous SP exercise, but it is based on an orthogonal design. The reason for this different approach is that one of the two design variables (i.e. the probability of an increased price in the future) is not directly associated with an estimated parameter. Instead, it is used to define the expectation of the possible future outcomes and has an indirect influence on the estimates of the other two parameters. The methodological framework that is applied in this case is based on Expected Utility Theory and it will be discussed thoroughly in Chapter 4.

Table 3.3: Comparison of simulation methods for the Bayesian efficient design

Simulation Method	PMC	Halton sequences	Sobol sequences	MHLS	Gaussian quadrature
			D – error		
Fixed	3.38	3.20	***3.19***	3.33	3.20
Bay. mean	3.53	***3.36***	***3.36***	3.50	***3.36***
Bay. std dev	0.35	***0.29***	0.30	0.31	***0.29***
			t-ratios of prior estimates		
Price	***1.27***	1.12	1.15	1.10	1.12
Ch. Duration	0.04	0.04	0.04	***0.05***	0.04
Walk time	0.49	0.48	***0.54***	0.48	0.48
Start time	0.26	***0.31***	0.30	0.27	***0.31***
			Pearson correlation (mean)		
	0.35	0.32	***0.30***	0.35	0.32
Design search procedure					
Number of random draws: 1000 (PMC, Halton, Sobol, MHLS), 4 abscissas (Gauss)					
Choice situations: 9			Choice model: MNL		
Constraint: Sequential orthogonal design			Search algorithm: RSC (only swapping)		
Efficiency measure: D - error					

As it was mentioned earlier, there are three attributes in the booking game, and each attribute is assigned with three levels. Thus, a full factorial design would consist of 3^3=27 combinations. In order to examine a wider range of the probability attribute it would be necessary to test 5 levels (two above and two below 50%) leading to a full factorial of $3^3 5^1$=45 combinations or even 5^3=125 combinations if the expected price levels were also increased for a balanced design. Since it was decided to have three levels of price probability and the middle value of 50% is intuitive, the remaining two levels (20% and 80%) were selected arbitrarily but under the deliberation that they are not neither too close to the average value nor too extreme to have a deterministic effect on the final choice.

In order to simplify the choice task for the respondents, a fractional factorial design is used which contains only a subset of those possible combinations. Assuming that the interaction terms are negligible (Street et al., 2005) an orthogonal design was found with the use of the Ngene software that enables the uncorrelated estimation of all main effects. The final design, as with the charging game, contains nine choice situations.

3.4 Survey pilot and focus group

Before the full-scale administration of the survey instrument, it was first outsourced to SRA Ltd[26], a firm with strong experience in conducting travel-related surveys, in order to pilot it with a small sample of 19 respondents. The EV-PLACE survey was administered to those people online in order to test it under the conditions that were planned for the final sample (i.e. self-administered without the assistance of an interviewer). Since both choice experiments provided respondents with nine choice situations, two datasets with 171 (19x9) observations were generated.

For the pilot, the two SP exercises were statistically designed with the use of a fractional factorial orthogonal design: for the charging game in order to estimate the priors that would be used for the efficient design later, and for the booking game because an efficient design was not feasible anyway. The design variables that were used for the charging game were the same in the pilot and the final design; however minor changes have been applied to the attribute levels that will be explained later. On the other hand, the design variables for the booking game were originally four. The extra attribute, i.e. the probability of finding an available charging post later, was dropped for the reasons discussed earlier in this chapter.

After the completion of the online survey, we conducted a focus group with eight of the 19 respondents. The focus group meeting was held at the Centre for Transport Studies at Imperial College London and it was organised in collaboration with SRA Ltd. While the people taking part in a focus group do not constitute a statistically significant sample, this meeting was ideal for generating insights into the effectiveness of the employed survey tool. In particular, the objectives that we aimed to accomplish with this focus group were:

1. Validate the reliability of the collected information and, consequently, the unbiasedness of the estimated models.

[26] SRA Ltd, Director: Kristine Beuret OBE, FCILT, FICHT, TPP, MMRS. Leicester Office: 2 Princess Road West, Leicester LE1 6TP. London Office Unit 3, 4 Archie Street, London, SE1 3JT. http://www.sraltd.co.uk/

2. Understand if the instructions for the choice experiments convey the desired message, and if not, identify ways to refine them through the conversation.
3. Assess the avatar (proxy character) methodology that was initially implemented and the level of the respondent's connection to this artificial person as well as the level of engagement to the decision-making process.
4. Explore the possibility of complications with jargon or complex terminology (e.g. dynamic pricing, probabilities for future prices) and discuss ways to simplify them.
5. Collect feedback for the survey's interface (e.g. structure, navigation methods etc.) and for frequently anticipated technical problems

The discussion was summarised in 11 questions that are presented in Appendix A. The survey was projected to the participants during the meeting in order to highlight the particular points and identify the potential problems. In the beginning, participants were introduced to the benefits and limitations of owning and driving an electric vehicle, since none of them had experience with EVs in the past. The target of this initial discussion was to set the context of out-of-home recharging before getting into the details of the survey tool.

Regarding the complexity of the choice games and the level of success in conveying the required message with the given instructions, there was a unanimous request for further clarification. For example, one participant said: "There is lots of reading. Big sentences, some of them I don't read. Sometimes I got a little bit lost between the questions and the pictures" while another, commented: "First reaction: That's overwhelming! Too much to read. Too much information. I wasn't paying attention at all, I just started skipping the pages".

Moreover, the comments of the participants shed light on factors associated with the presentation of the SP exercises. For instance, the choice situations of the charging game were first presented in a different way, as it can be seen in Figure 3.5. Instead of using the interface of a hypothetical online application as it was demonstrated earlier, each choice was separated into three parts: a graphical presentation of the daily schedule and the driving distances, a demonstration of the battery level before and after the charging event with the use of gauge indicators and finally a table with a list of the charging attributes for the two alternatives.

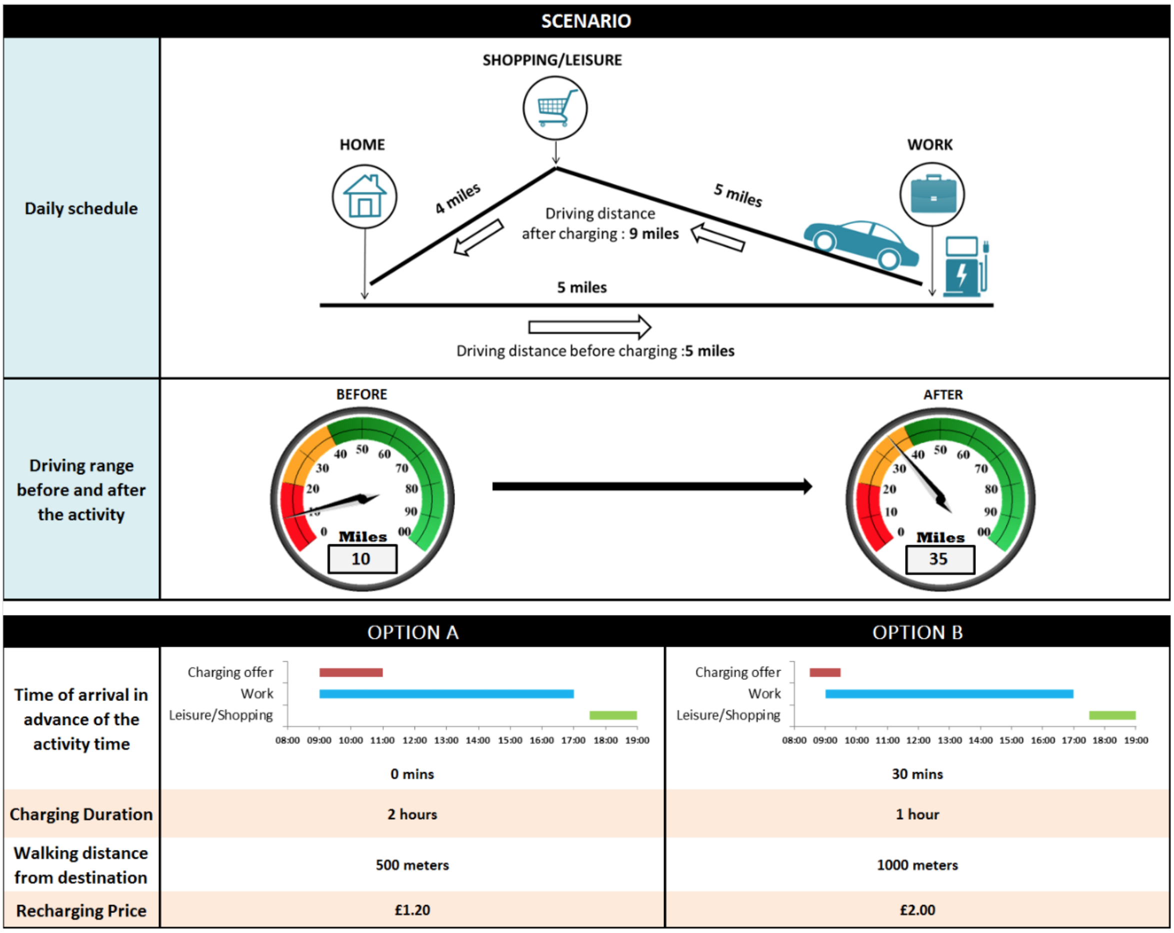


Figure 3.5: Preliminary presentation of the charging game, before the pilot and the focus group

The participants expressed their concerns about this presentation style. One said: "I can't understand if the gauges are related with the two charging options" while after the discussion another one added "Now it seems so simple! But you have to think a lot about what is represented". According to the majority of the group, the fact that both charging options were offering the same amount of energy was not conveyed clearly. A participant commented: "You have the idea that if you are charging for more hours, you will get more out of it. That might be from not understanding that the total charge is going to be the same".

There was also an attempt to suggest alternative ways in order to improve the level of engagement with the game: "The triangle is not a really good way to show this (the daily schedule). My eye has to go to two things. If there was a clockwise arrow you could integrate the "before" and "after" gauges in this image. I am only trying to extract one piece of information. Also, there is not a marker on 35 (range indicator). You should give them the number, making the arrow point at it". The coordinator from SRA Ltd, who had a personal discussion with some of the respondents after they completed the survey, indicated "When people said there is too much information they didn't mean words, they meant overload of everything, diagrams, pictures and all of it."

Some of them claimed that using meters to express the distance from destination was not straightforward ("I don't understand the 1000 meters. I don't know how far that is. How long would that take me to reach my destination?"), since walking time could be influenced by the spatial setting ("Is it up the hill? Is it down to Oxford Street?"). There was also a sense of misunderstanding around the visualisation of the time schedule and how the charging offer fits into it. The idea here was to use coloured bar charts (Figure 3.5) so that if the individual is required to arrive earlier than his preferred arrival time, it can be easily detected in the choice card. However, one of the participants said, "If you are charging you can't be at two places. If you drop the car at 09:00 am you would need to be working at the same time" and another added "At first I thought I would have to go back and get the car. I am only charging for an hour, but I am parking here for eight. Unless there is a system that someone else moves your car afterwards".

Preliminary estimation based on the pilot sample showed that the most significant parameter in the charging choice was the difference between the starting time of the activity and the starting time of the charging offer. This was obvious in some of the comments: "What's £2.00 and 60p in a world that you pay £4.00 an hour to park your car somewhere in Central London. Compared to the cost of motoring this is just so trivial. The only thing that had any consequence on me was time. My time is more valuable to me than anything else. I don't want to be inconvenienced by my car, ever". The expected insignificance of the charging duration parameter was confirmed both from model estimation and the focus group discussion. One person commented, "If I am at work why do I care how long my car charges?" while another agreed, "I didn't understand the relevance of charging duration."

Concerning the underlying reservation system that is described in the instructional section, a participant argued: "I would be happy just to be told that the company built a nice bit of software where you book. I don't see how this is relevant in answering the question unless the question was formatted using a similar type of interface". Including a demonstration page of the booking application, without allowing respondents to try-out the parameters was also misleading "I thought this page was really confusing. I couldn't understand what I am supposed to do with it. You could just go straight into the game and you would understand what's happening".

Before starting the charging game, the respondents were originally introduced to a "proxy character" with similar socio-demographics and they were told that their role was to advise this character on how to charge his/her EV. In general, it is difficult to validate the realism of stated choices when there is a low degree of familiarity with the choice situations, or respondents do not perceive them as applicable to their case. The purpose of this method was to disassociate the individuals from the choice process since they were not driving an electric vehicle and hence the scenarios presented were not characteristic of their daily schedule.

However, according to the literature, people tend to behave differently when they advise others than when they make personal decisions. For instance, in the first case, they may consider fewer sources of information, engage in risky choice situations, or form an incomplete picture of the advisee's preferences (Le Vine et al., 2011). Stated responses for another person become suitable replacements for actual choice information by increasing the concreteness and vividness of this person (Kray, 2000). In this direction, the mental overlap between the respondent and the "proxy character" was increased by introducing a resemblance in their personal attributes (e.g. age, gender, employment status etc.).

The comments on the use of the avatar were ambiguous; yet, the general impression was that it was redundant (" In a way you already project yourself into it [the choice situation]. That's the nature of what it is. For brevity it could reduce the wording quite a lot") and sometimes disorienting ("This is what you want to know. What we think. You don't want to know what Jack [the avatar] would do. Do you?").

The part of the survey that was related to the booking game received mainly positive feedback, and it was not considered necessary to proceed with major modifications. Regarding the airline booking analogue and its importance in understanding the context of dynamic pricing for charging services one participant commented, "I thought this was a really good comparison. I got instantly frustrated because I get frustrated about flights. It's guaranteed that you are going to lose. Someone is going to get a cheaper price than you and you are going to hear about it".

Choice outcomes revealed a preference towards the booking-now alternative and hence an underlying risk-averse behaviour in booking decisions. This was supported by the discussion during the meeting ("I thought I am just going online and I want to do it now. I don't want to wait a day to save a pound", "I would forget to come back later", "I would never play some weird game about gambling").

Particular attention was given in how respondents perceived the probabilities of future prices during the booking game. It has been underlined in the literature that conveying the likelihood of a certain event occurring as well as the consequences of this occurrence is far from a straightforward task. Bates et al. (2001) have stated: "While for the analyst this is implicit in the concept of a probability distribution, most non-statisticians do not see things that way!". According to Kreye et al. (2011), when respondents are presented with a probability distribution of possible future outcomes, they tend to simplify their decision by choosing the average value or the most likely one.

Alternative presentational methods have been suggested in the public transport reliability area. For example, instead of showing the actual probability values, a researcher could use the following formulation: "one in ten times, attribute X is larger than Y". However, this could lead to variation in interpretation as people may perceive in different ways what is going to happen in the other nine times.

Another widely adopted technique is to present respondents with a range of possible outcomes. For example, lateness in the case of public transport can be depicted with a series of patterns (e.g. 0,0,0,0,0,5,5,10,15,20 minutes is a pattern of delays with ten occurrences). Black and Towriss (1993) have piloted the presentation of reliability in travel times, showing that the best results emerged when arrival times were expressed in minutes earlier or later than the mean arrival time and ordered accordingly. Small (1999) made explicitly clear to the respondents of the SP experiment that the presented occurrences of arrival times were *equally likely*.

Bates et al. (2001) tried to reduce the unintended bias causes when ordering these occurrences from left to right[27] by designing a circular, clockface format. In order to assess the respondents' level of understanding they first presented them with some "tests" where they had to identify the most punctual pattern (i.e. the one with the lowest standard deviation). Those who have shown a tendency to incorrect responses were excluded from the analysis.

[27] It was observed that respondents perceived this as a chronological order, resulting into some of the infrequent travellers discounting the higher values on the right.

Kreye et al. (2011) carried out an experiment to identify the effect that different graphical presentations have on participants' awareness and interpretation of uncertainty. In this experiment, participants were divided into three groups and each group was presented with one of the following variations: a three-point trend forecast, a bar chart and a fan diagram. The results indicated that the fan diagram has raised the highest level of awareness for the underlying uncertainty, even though respondents were less familiar with it than with the other graph types.

Due to the aforementioned difficulties in the presentation of uncertain outcomes, three additional visualisations of the expected future prices were produced: two variations of bar charts demonstrating the range of possible outcomes and one cyclical format, based on the presentation of Bates et al. (2001). During the focus group, participants were shown a slide with the four alternative styles (including the actual probabilities used in the booking game) in order to elaborate on their advantages and disadvantages (Appendix A). The participants came unanimously to an agreement that the original presentation was the most comprehensive. In particular, one said, "I thought that this was a really good visual link because of the flight comparison. I wouldn't need anything else".

After assessing the pilot results and the valuable insights gained from the focus group, it was decided that with the proper modifications, the Internet-based survey tool could be self-administered without the use of CAPI (Computer Aided Personal Interview) methods. In this way, it would be possible to achieve a larger sample size and hence more significant estimates of the charging parameters.

The alterations in the EV-PLACE survey, after the piloting stage, were in line with the objectives set for the focus group meeting and the problems that were stressed by the participants. In particular:

1. The confusing triangular representation of the daily schedule was replaced with a cyclical one (as it was shown in subsection 3.2.1) and the time-frame for profile choice was generalised from "previous day" to "one day of the past week" so that respondents have more flexibility in finding a travel pattern that suits them best.
2. The avatar methodology was dropped because an unintended level of engagement bias was introduced in place of the EV experience bias. Moreover, the narrative around this hypothetical character was placing an additional burden to the already complex survey tool. Thus, after full-scale deployment, respondents would have to

complete the two SP exercises for themselves, assuming that they own an EV and need to charge it out-of-home. This can be partly justified by the fact that a significant proportion of the final sample consists of EV drivers.

3. The demonstration of the hypothetical reservation system along with its text-based description was removed from the survey. Instead, both the charging and the booking game were redesigned with an online application interface and an instructional video was created for each of them, where respondents were guided to the choice situations with the use of a voiceover.
4. The attributes of interest were highlighted during the instructional video so that respondents have a clear view of the trade-offs that they have to make when they compare the charging alternatives.
5. It was clarified to the respondents that the charging amount is always the same for the two alternatives and, therefore, longer charging durations do not result in higher battery levels. Moreover, it was explained that after the vehicle is plugged-in there is no need to return to the parking facility unless your activity is over.
6. Deviations from activity schedule (schedule delays) were slightly reduced since it was observed that they were overruling the other attributes during the choice process. Simultaneously price levels were increased, a decision that is justified by future energy prices and implementation of demand-side management strategies. Finally, the walking distance attribute was converted to walking time because the latter provided a direct connection to activity timings.
7. Task complexity was partially addressed by emphasising important points with bold and larger fonts.
8. A new set of attitudinal (Likert-scale) questions were added to the survey in order to elicit unobservable behavioural aspects that might affect the charging choices (e.g. schedule flexibility, parking strategy, satisfaction with the EV etc.).

3.5 Survey administration and sample recruitment

The decision to use a self-administered Internet-based survey tool was taken after a cross-examination of the alternative state-of-the-art methods. The advantages and disadvantages of each method are indicated in Table 3.4.

Table 3.4: Advantages and disadvantages of various survey administration methods

	Face to Face	Telephone	Internet	Mail
Validity check	+	+	-	-
Measurement error (different responses from same people)	+	+	-	-
Non-coverage error	+	+	-	-
Non-response error	+	+	-	-
Compliance factor	-	-*	+**	+
Anonymity breach	+	+*	-	-*
Complexity allowance (visual aids and control over pace)	-	-	+	+
Cost	-	+	+**	+
Sample size	-	-	+**	+
Response time	-	-	+**	+
Monitoring and recording completion patterns	+*	+*	+	-

* There is a possibility that these factors are not advantageous (or disadvantageous) for this administration type.

** These factors might be compromised when an Internet-based survey is administered as CAPI

Complexity allowance and large sample size were the most important factors for this thesis and after conducting the focus group it was considered realistic to proceed without the involvement of personal interviewers. Moreover, the possibility to monitor and record completion patterns, like the tempo with which the respondents move through or the amount of interaction with the survey instrument (e.g. when they search for a travel profile) is very important here, in order to capture their adaptation to complex elements.

The main drawback of the online-administered tool is validity check, i.e. the difficulty in conveying the prerequisite information to the respondents, especially for the two SP exercises. The strategy adopted in order to overcome this issue was to identify the weak points throughout the piloting stage and modify them according to the respondents' feedback. Furthermore, there is a higher probability for a non-coverage error, due to the exclusion of electric vehicle drivers that do not have Internet access. However, it is assumed that Internet usage rate is high among early adopters of new technologies, like EV drivers.

The final sample formation was based on a mixed recruitment strategy, i.e. a combination of EV drivers recruited by the researchers and a panel of EV and non-EV drivers recruited from Panelbase.com[28], a major provider of sample services for online surveys.

Panelbase.com has over 200,000 adult members that are engaged in various online and offline surveys and are profiled according to their characteristics. Initially, those panellists are recruited either after telephone interviews or through affiliate websites. In order to select a panel for a specific survey, the profiled information is used to create a targeted base. Then, the unique id's of people that qualify for the survey are randomised and invitations are sent to a randomly selected group of this "target base".

Participants were incentivised to complete the survey by automatically entering a raffle for three £200 vouchers for online shopping after submitting their responses. Incentives in web surveys, either monetary or non-monetary, are useful in order to increase the response rate but very little is known about their effect on non-response bias. In particular, promised non-monetary incentives (like coupons or vouchers) have apparently better results for online than offline surveys. It is likely, though, that this is due to their frequent use and the fact that Internet users have come to expect them instead of pre-paid monetary incentives that have been largely used for offline surveys (Bosjnak and Tuten, 2003). One potential shortcoming is that respondents will be intrigued to complete the survey many times in order to increase their probabilities of winning the raffle. However, this has been prevented by using a list-based methodology, i.e. participation was subject to an invitation by the researchers and only one completion was allowed (Comley, 2002).

The ideal target population for the EV-PLACE survey was that of EV drivers in the UK[29] because they have both familiarity with the technology and an understanding of recharging needs when choosing among the hypothetical charging offers. By the end of 2014, the number of licenced plug-in cars and vans in the UK was approximately 21,000 (RAC Foundation, 2015). Considering that the total number of licenced vehicles is 30.5 millions, this accounts for 0.06% of the total population. Obviously, the challenge in finding and recruiting a significant sample from this small proportion is high.

[28] Panelbase.com, Director: Angus Webb. Registered office: The Mill, Hexham Business Park, Burn Lane, Hexham, Northumberland, NE46 3RU. www.panelbase.com

[29] By EV in this case we mean all types of vehicles that can plug-in and recharge using energy from the power grid (Battery electric vehicles, Plug-in Hybrid electric vehicles, Extended range electric vehicles etc.).

First, it was attempted to contact several EV driver associations and forums in the UK. Here is a list of those that responded and contributed with the participation of some of their members: Battery Vehicle Society, EV Scotland, EV network, EVDA-UK, EVSpeak and ElectrAA. However, the total number of respondents from this recruiting channel was relatively low (35 individuals).

Furthermore, it was considered that participants of electric vehicle trials would be ideal candidates since they could have the experience required in driving and charging a plug-in vehicle. For example, 25 drivers in London have been leased a Nissan Leaf for one year as part of the Low Carbon London project. These drivers have been involved with earlier research projects at Imperial College London and 12 of them have agreed to be re-contacted for potential future surveys. Invitations for the EV-PLACE survey were distributed to them and seven (58.3% response rate) provided complete responses.

Likewise, there was the possibility to extend the scope of the research outside the UK by recruiting drivers that have participated in the Great Electric Drive trial launched by ESB Ireland. ESB has collaborated with EU projects (e.g. Green eMotion, Mobi.Europe etc.) in order to collect information on EV consumer behaviour and analyse the existing charging infrastructure. The trial included passive data collection via GPS and data loggers as well as focus groups, pre-experience and post-experience questionnaires. Our survey has been slightly adjusted to accommodate non-UK respondents and invitations were sent to 16 individuals. A response rate of 56% was achieved in this case.

The complexity of the survey tool (i.e. long duration and high level of engagement required) as well as the need to contact the researchers directly and obtain a unique "token" (password)[30] needed for participation might be some of the reasons for the low number of individuals expressing interest. In conjunction with the already limited pool of EV drivers, the need for additional recruitment channels has emerged.

Social media, like Facebook and Twitter, could offer high visibility and fast proliferation at the expense of a potential loss in reliability. A link of the survey along with some basic information on the underlying research was posted on Twitter accounts of various EV groups and organisations (e.g. eco-cars.net, POD Point, Next Green Car, Ecotricity etc.). As it was

[30] In Limesurvey, which was the tool employed and the hosting server for our online survey, it is possible to hide the content from people that have not been provided with a unique password. This allows the proper monitoring and control after administration and the prevention of undesirable situations (e.g. repetition of the survey from the same person or participation from people out of the targeted population).

expected, the “snowball effect” worked due to the thousands of followers for each of these groups, and this post was re-tweeted in several accounts. Although people showed enthusiasm in promoting the survey, and quite a few requested a password to participate, the quotas of the complete responses were far from satisfying. In fact, all the recruiting methods described above provided a total of 47 responses.

With the available resources and the restrictions of the existing population of plug-in cars, it was impossible to achieve a representative variability in EV driver demographics. As a result, the sampling frame for this internally recruited segment was only constrained by the EV ownership condition.

The limiting requirement of owning or leasing an electric vehicle has been initially chosen for obvious reasons. In order to obtain reliable information on how people charge their EVs out-of-home and how they would change their charging behaviour under hypothetical scenarios, a certain level of familiarity with the charging process (even if it only included home charging) would be essential. Nevertheless, after the first stream of recruitments, it was decided to relax this requirement and contact Panelbase.com in order to increase the size and the representative variability of the sample.

The above relaxation was achieved by accepting as eligible for participation not only people who drive an EV but also those that “have seriously considered buying one during the last 12 months”. Of course, it is difficult to quantify the level of trust that can be placed on this statement, especially when panellists are given financial incentives to participate in online surveys. For this reason, the so-called “considerers” were asked to write which specific model they would prefer, and in case they were not aware of any plug-in model they were excluded from the analysis.

The significant increase of the target population after this relaxation of constraints allowed for an additional constraint to be imposed, which was considered crucial for this research. Panellists were asked if they “needed to drive and park regularly in urban areas” and if they didn’t they were excluded from the final sample. The nature of the SP experiments and the interest in analysing joint parking and charging choices presumes that the respondents can empathise with the difficulties associated with finding a parking place in urban environments. For someone who lives and commutes in a rural area, the scenarios presented in the games are most likely not applicable, and hence, the choice outcomes would be unrealistic.

Both questions described earlier were presented to the panellists in a pre-screening questionnaire and those who qualified for these criteria were considered for sample selection. The representative variability in demographics is achieved through the randomization process that Panelbase.com follows. 9.3% of the randomly selected respondents fulfilled the aforementioned criteria and were redirected to the EV-PLACE survey. The sample from this recruitment channel consists of 98 EV drivers and 118 "considerers" and as a result the final sample size is 216. The surveys were completed between 19/05/2015 and 03/06/2015.

The breakdown of the various recruitment channels according to their characteristics as well as their respective response rates are collectively presented in Table 3.5.

Table 3.5: Characteristics of recruitment channels for the EV-PLACE survey

	EV driver associations and forums	**Electric vehicle trials**	**Social media (Facebook and twitter)**	**Panelbase.com**
EV experience	All	All	All	Some of them
Licence holders	All	All	All	All
Sample representativeness	No	No	No	Yes
Knowledge of population from which sample is drawn	No	Yes	No	Yes
Geographical coverage	UK	UK and Ireland	UK	UK
Response rate	57.1%	57.1%	N/A*	60.2%
Sample size	20	16	11	216

*For this recruitment channel, it is possible to calculate the completion rate among people that contacted the researchers in order to get access to the online survey. Nevertheless, it is very difficult to estimate the total number of individuals that had access to the survey invitation originally.

3.6 Descriptive analysis of the survey data

The demographic characteristics of the 263 respondents are presented in Table 3.6. A direct comparison with the ideal sampling frame is not possible due to the lack of information about the population of EV drivers in the UK. On the other hand, comparison with car owning drivers would not be accurate because of the unique characteristics that early adopters present. Therefore, it is difficult to evaluate the representativeness of the sample. However, it is possible to examine the differences between the EV drivers and the EV considerers, the UK-based and the Ireland-based drivers, and finally, the respondents recruited by the researchers and those recruited by Panelbase.com.

Some of the main conclusions with respect to the demographics of the EV-PLACE survey are[31]:

- There are more men than women especially among EV drivers and among the internally recruited respondents.
- More than 65% of the respondents belong to the 20-39 age group, mainly due to their over-representation in the panel group. The age is more evenly distributed for the internally recruited group.
- The majority of the respondents are married or they live with a domestic partner. Moreover, the percentage of those that have children and live with them is higher for the "EV drivers" than for the "EV considerers" group.
- 70% of the respondents are employed full time. This proportion is larger for the panel group (73.3%) whereas people from other recruitment channels are more likely to be self-employed (10.9%) or retired (19.6%).
- 43.7% of the respondents live in London and 56.3% live across the rest of the UK and in Ireland. However, the ratio of EV drivers is higher in London (53.1%) than elsewhere. The spatial allocation of the sample is characterised by considerable variability as it can be seen in Figure 3.6.
- The majority of EV drivers (81.4%) have access to an additional petrol/diesel vehicle that they can privately use.
- The percentage of people living in a house or bungalow is higher among EV drivers (76.6%) than among EV considerers (65.3%). This could be potentially associated with the recharge opportunity that an off-street parking place offers.
- Almost half of the respondents live in households with at least four residents. This proportion is significantly higher for the panel group (53%) than for the rest of the sample (30.4%).

[31] The differences between the UK and the Irish sample are not commented because of the small size of the latter (10 respondents).

- The predominant ethnicity in the sample is "White" (74.1%) with "Asian/Pacific islander" coming second (15.2%).
- The education level[32] is slightly higher for EV drivers than for the other respondents (64.2% combined graduates and post-graduates among EV drivers vs 58.4% among EV considerers).
- Likewise, the income distribution is more skewed towards the higher end for EV drivers compared to EV considerers (42.8% vs 21.2% belong in the "high" and "very high" income bands[33]).

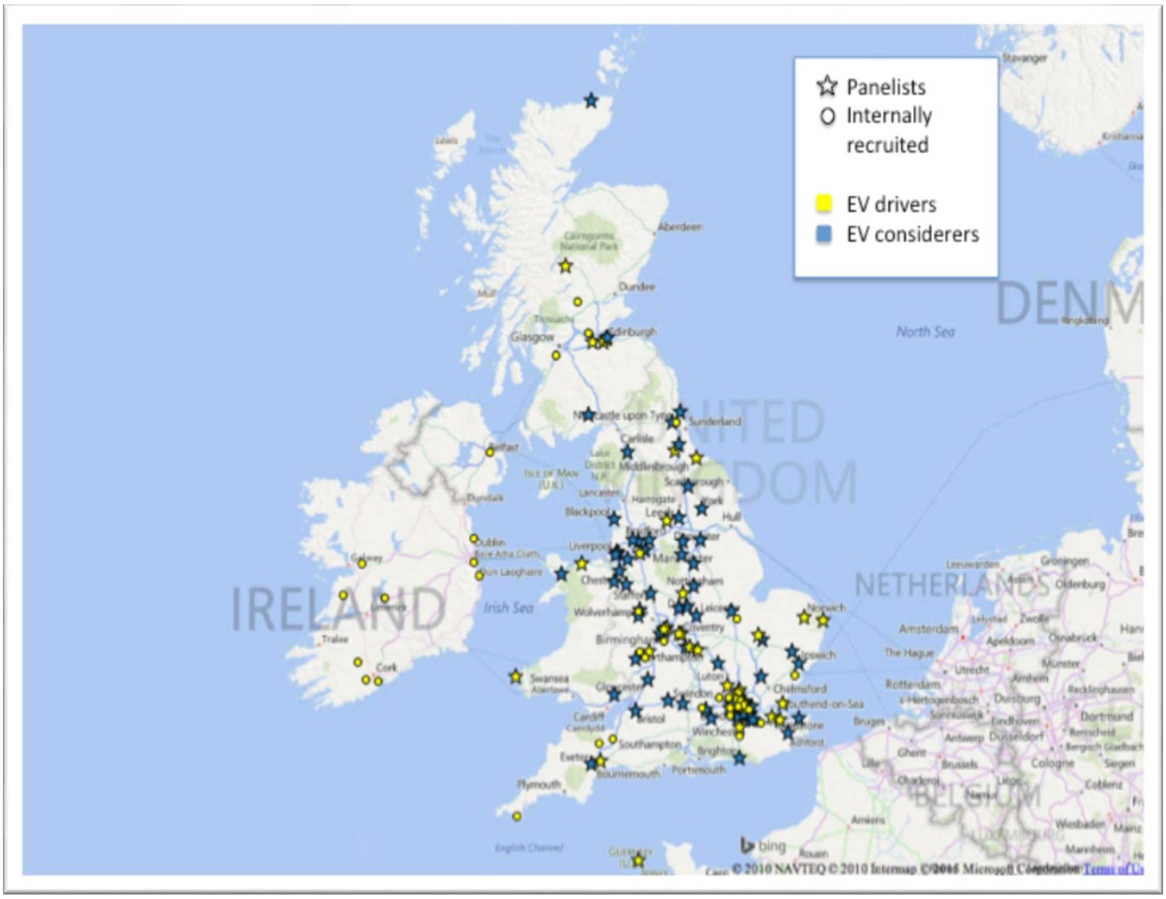


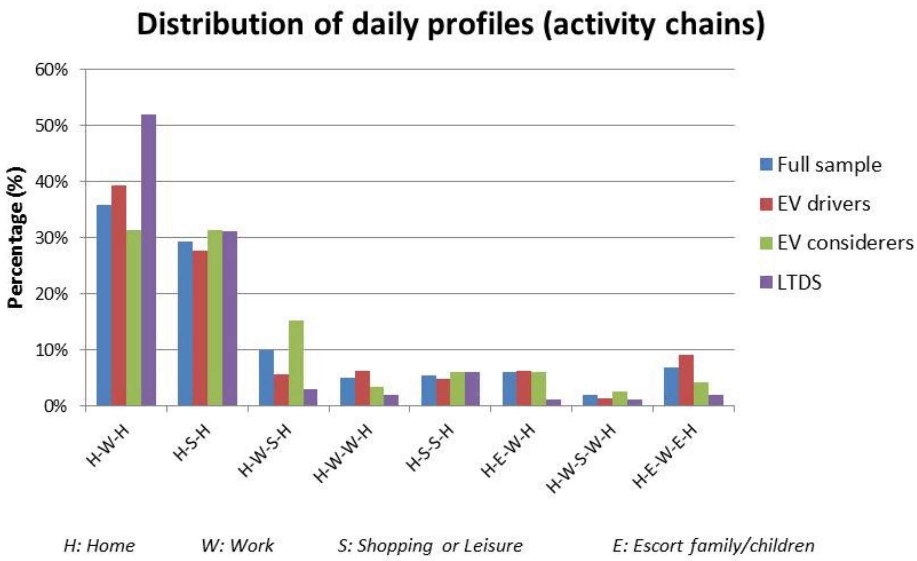
Figure 3.6: Location of EV-PLACE respondents in UK and Ireland

Figure 3.7 shows the travel profiles selected by the respondents when they were provided with the most representative alternatives based on their demographics. As it was described earlier in the chapter, these profiles were afterwards used for the choice scenarios of the SP

[32] The responses to the question "What is your highest education level?" for UK participants were: 1: GCSE or equivalent, 2: A level or equivalent, 3: Graduate, 4: Post-graduate and 5:other. Nevertheless, they were transformed into the categories of Table 3.6 so that they can be merged with the education levels for Ireland

[33] The income bands for UK participants were: 1: £10,000 or less, 2: £10,001-£20,000, 3: £20,001-£40,000, 4: £40,001- £70,000, 5: £70,001 - £100,000 and 6: More than £100,000. The same bands have been used for Ireland but with a different currency and hence, the final transformation can be seen in Table 3.6.

experiments. Most of them have chosen either the Home-Work-Home or the Home-Shopping/Leisure-Home daily tour, which is aligned with the actual travel patterns of London drivers in LTDS. When asked for which day of the week they have selected this profile, most of the respondents answered Monday, while the next most common response was Wednesday.



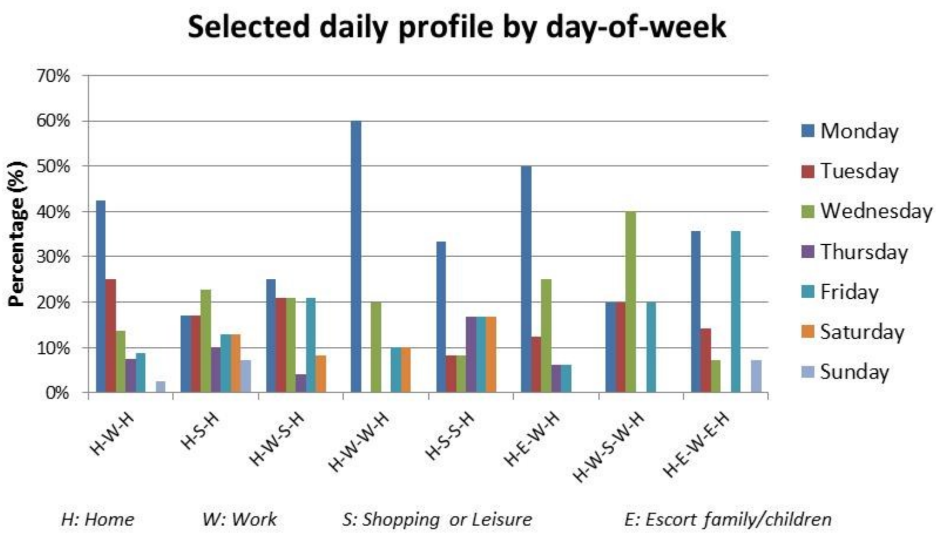


Figure 3.7: Travel profiles of the respondents based on their preferred activity chains

Of the 145 electric vehicle drivers, 128 own their vehicle, 12 lease it, 3 have a personal contract purchase (PCP), one uses it as a company car and another one is borrowing it from a friend. Almost half of them have been driving their EV for less than 6 months, whereas approximately 25% have the experience of driving an EV more than a year. Their driving characteristics are presented in Figure 3.8. In this figure, it can be observed that almost 40%

of them use the EV for their everyday travel while another 35% use it between 4 and 6 days a week. The typical daily mileage reported by the respondents shows that problems with the range of the battery are very unlikely since only 10% drive more than 40 miles per day. Finally, the daily cost for recharging, as it is perceived by the EV drivers, follows a normal distribution with the majority paying between 50p and £2.00.

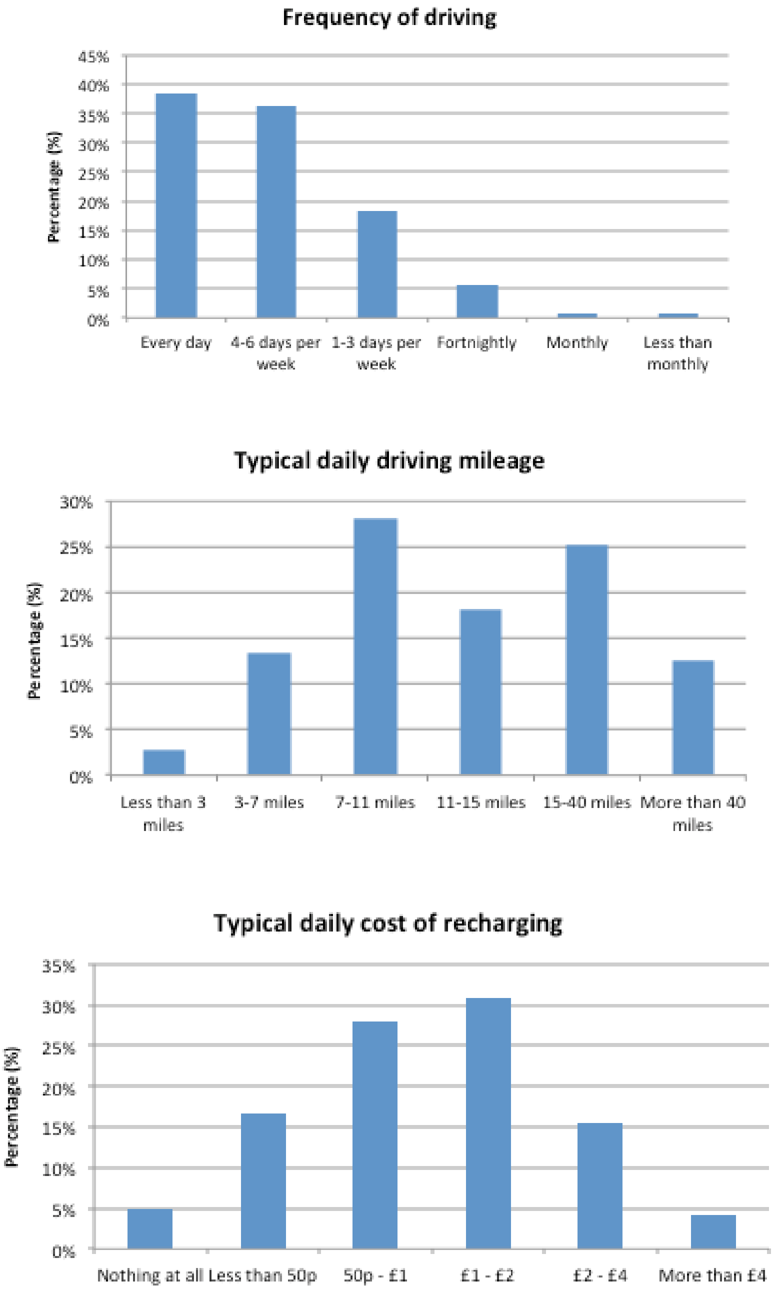
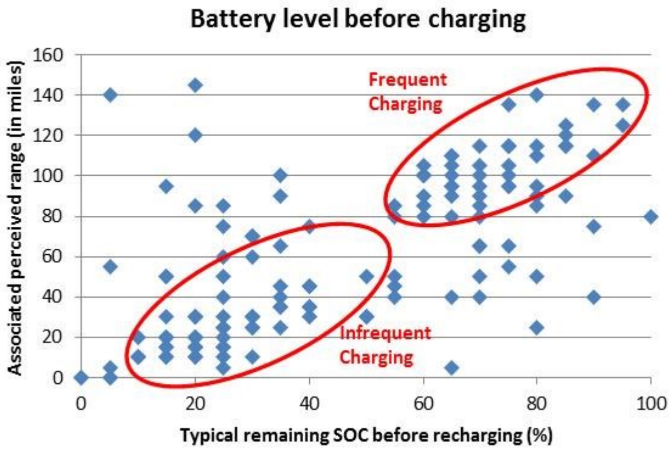


Figure 3.8: Driving characteristics of respondents that own or lease an electric vehicle

The first graph of Figure 3.9 indicates the SOC that triggers the initiation of a charging event from the respondent. Individuals were first asked to provide a value for the typical battery level before they plug-in their vehicle. Then they were asked what is the associated remaining driving range for this battery level. As it is highlighted, there are two types of drivers: those who prefer frequent charging (initial SOC above 50%) and those who prefer infrequent charging (initial SOC below 50%). It is plausible that those who belong in the first category are more risk-averse and more likely to demonstrate “range anxiety”. On the other hand, the outliers of this graph show a certain level of misperception regarding the transformation of SOC to driving range.



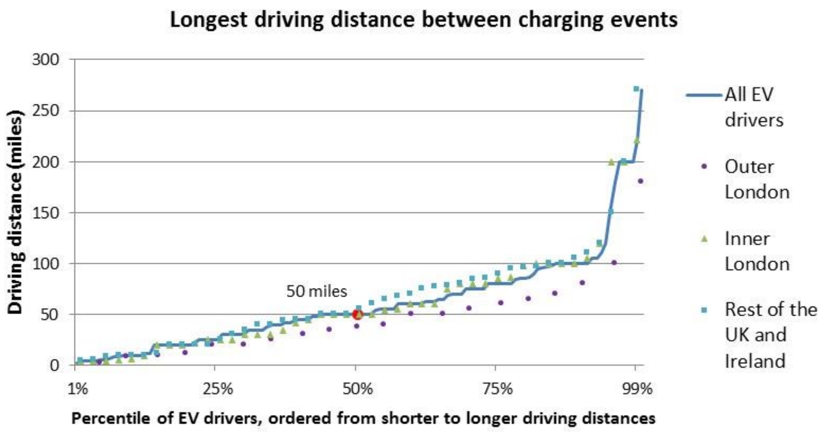


Figure 3.9: Charging preferences of EV drivers in the sample

In the same figure, it is interesting to observe that most of the respondents (80%) have a charging opportunity at home while 40% of them do not consider (or do not have access to) an alternative location. The longest reported driving distance between two consecutive charging events has similar patterns for varying geographic locations (i.e. inner London, outer London, rest of the UK and Ireland). The stated values are slightly higher for individuals that do not live in London, yet the median value is 50 miles for all cases.

Figure 3.10 shows that charging frequency is distributed quite uniformly, and a spike occurs for those that charge their EV once a day. According to the two pie charts in the same figure, the majority of the drivers are satisfied with current driving ranges and charging durations. On the other hand, 20% feel that they need higher battery capacity and faster charging infrastructure. Finally, a significant proportion of the recruited individuals are EV enthusiasts, whereas 1 out of 10 would not recommend their vehicle to a friend or colleague.

The final figure of this chapter (Figure 3.11) contains information about the users' opinion for the survey and their level of understanding. The description of the reservation system for charging services was considered quite efficient since only 7% said that they did not properly understand it. Likewise, 68% of the respondents found the airline-pricing example helpful in conceptualising a similar application for electric vehicles.

The capability of monitoring survey completion times was proven to be very significant for the analysis in this thesis. Contrary to the estimated survey duration (30-40 minutes), 75% of the respondents finished the questions in less than 25 minutes. Potential biases associated with random or less meticulous completions were isolated and removed from the final sample that was used for modelling charging choices in Chapter 4.

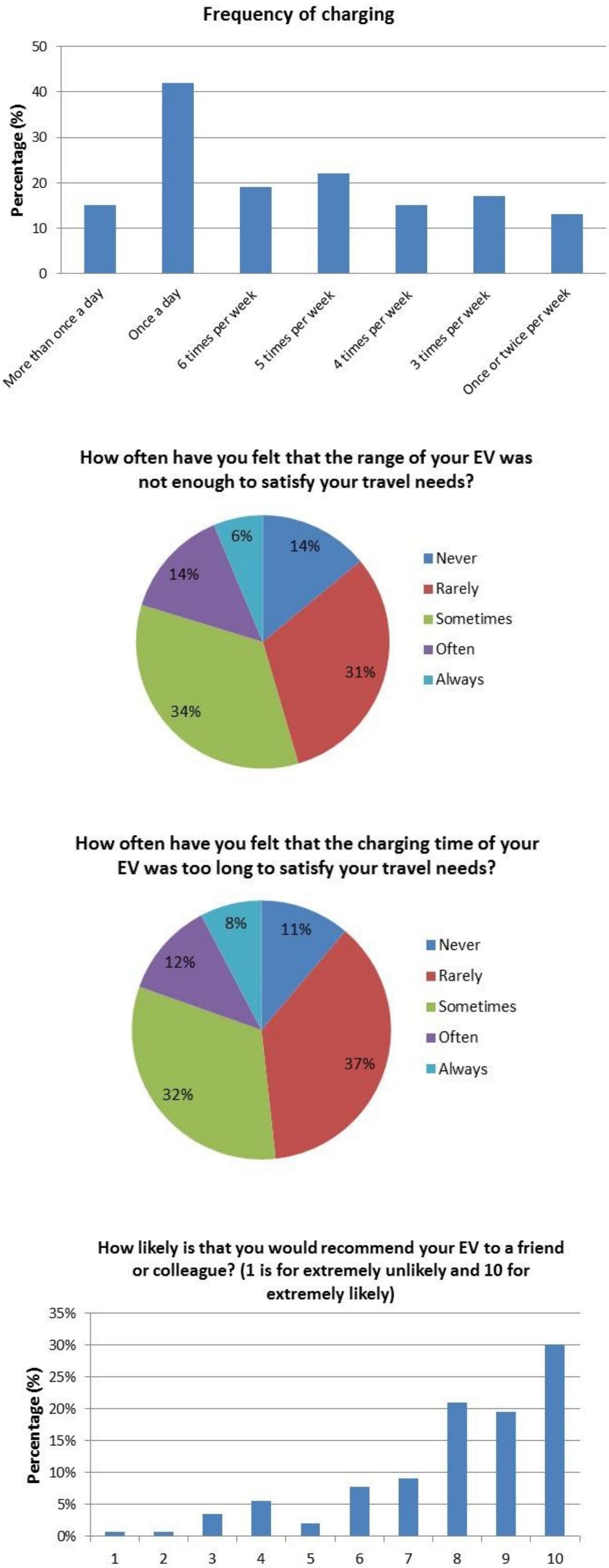


Figure 3.10: Additional characteristics, attitudes and perceptions of EV drivers

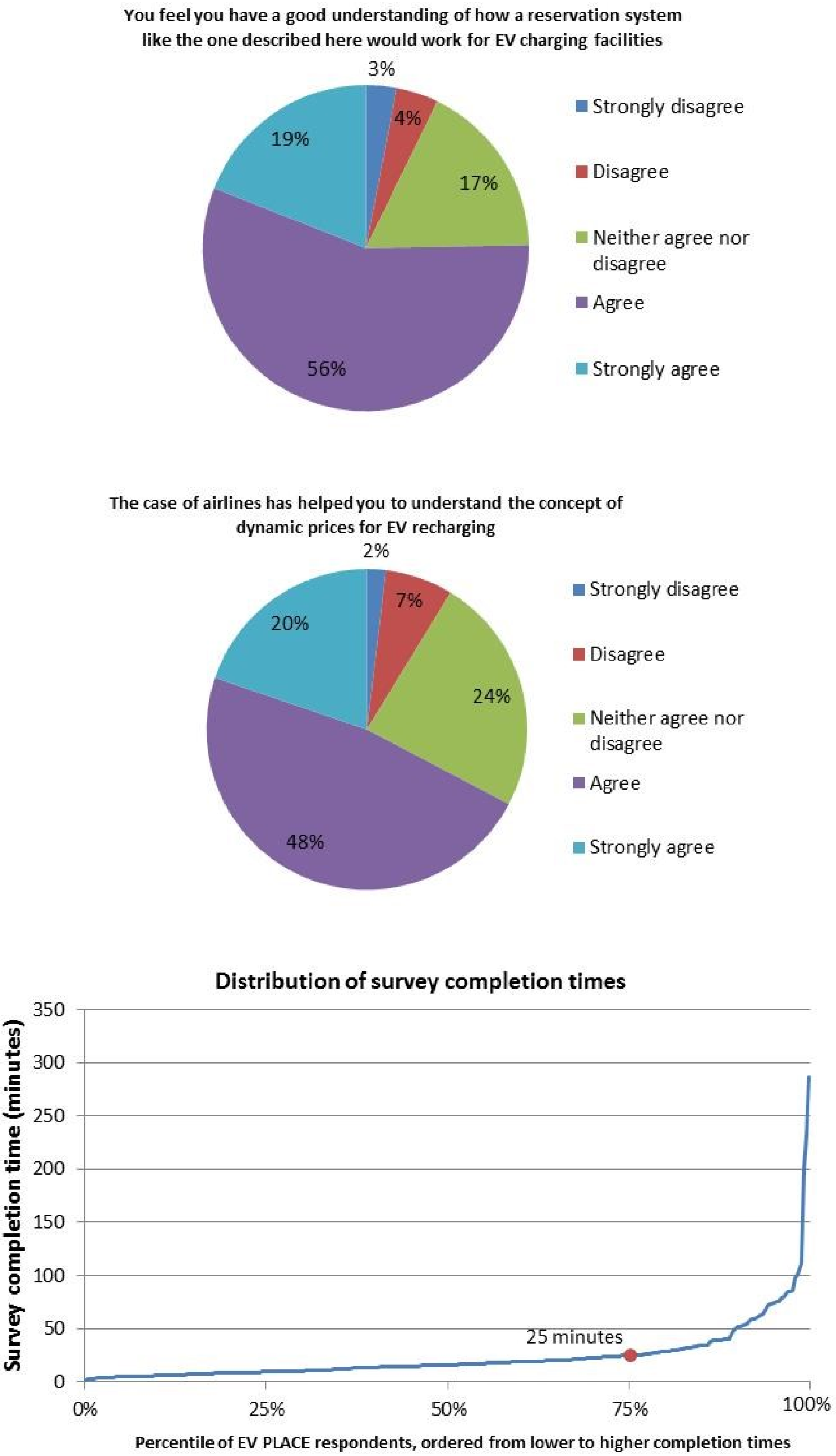


Figure 3.11: Perceived level of understanding about the EV-PLACE survey and completion times

Table 3.6: EV-PLACE survey demographics segmented by EV accessibility, place of residence and recruitment channel

Indicator	Full sample	EV drivers	EV considerers	UK based	Ireland based	Internally recruited	Panellists
Gender							
Men	65.0%	71.7%	56.8%	36.4%	100%	95.7%	58.5%
Women	35.0%	28.3%	43.2%	63.6%	0%	4.3%	41.5%
Age							
Less than 20 years old	1.9%	0.7%	3.4%	2.0%	0%	0%	2.3%
20-29 years old	35.0%	32.2%	38.1%	36.4%	0%	10.9%	40.1%
30-39 years old	31.2%	28.1%	34.7%	31.2%	30.0%	19.6%	33.6%
40-49 years old	17.5%	21.2%	13.6%	16.6%	40.0%	26.1%	15.7%
50-59 years old	9.1%	9.6%	8.5%	9.5%	0%	17.4%	7.4%
60-69 years old	2.3%	3.4%	0.8%	1.6%	20.0%	10.9%	0.5%
Over 70 years old	3.0%	4.8%	0.8%	2.8%	10.0%	15.2%	0.5%
Marital status							
Single, never married	32.7%	27.6%	39.0%	34%	0%	26.1%	34.1%
Married or domestic partner	63.0%	68.3%	57.6%	62.1%	100%	67.4%	62.7%
Widowed	1.1%	1.4%	0.8%	1.2%	0%	2.2%	0.9%
Divorced	2.3%	2.1%	2.5%	2.4%	0%	2.2%	2.3%
Separated	0.4%	0.7%	0%	0.4%	0%	2.2%	0%
Having children	55.9%	66.2%	43.2%	54.5%	90.0%	60.9%	54.8%
Living with the children	48.7%	56.6%	39.0%	47.8%	70.0%	39.1%	50.7%
Employment status							
Employed full time	70.0%	73.8%	65.3%	70.4%	60.0%	54.3%	73.3%
Employed part time	9.1%	6.2%	12.7%	9.1%	10.0%	4.3%	10.1%
Supervising other employees	50.6%	55.2%	44.9%	51.4%	30.0%	26.1%	55.8%
Small workplace	19.0%	16.6%	22.0%	19.4%	10.0%	15.2%	19.8%
Average workplace	42.6%	45.5%	39.0%	42.7%	40.0%	28.3%	45.6%
Large workplace	17.5%	17.9%	16.9%	17.4%	20.0%	15.2%	18.0%
Self-employed	4.6%	4.8%	4.2%	4.7%	0%	10.9%	3.2%
Student	5.7%	4.1%	7.6%	5.9%	0%	2.2%	6.5%
Retired	4.6%	6.2%	2.5%	3.6%	30.0%	19.6%	1.4%
Unemployed	2.3%	0%	5.1%	2.4%	0%	0%	2.8%
Unable to work	1.1%	0.7%	1.7%	1.2%	0%	0%	1.4%
Other	2.7%	4.1%	0.8%	2.8%	0%	8.7%	1.4%
Place of residence							
Inner London (Zones 1 and 2)	26.2%	37.2%	12.7%	27.3%	0%	21.7%	27.2%
Outer London (Zone 3 or more)	17.5%	15.9%	19.5%	18.2%	0%	10.9%	18.9%
Rest of the UK and Ireland	56.3%	46.9%	67.8%	54.5%	100%	67.4%	53.9%

Table 3.6: EV-PLACE survey demographics segmented by EV accessibility, place of residence and recruitment channel (Continue)

Vehicle access							
Petrol/diesel vehicle for private use	86.3%	81.4%	92.4%	86.2%	90.0%	69.6%	89.9%
Type of accommodation							
House or bungalow	71.5%	76.6%	65.3%	70.4%	100%	78.3%	70.0%
Detached	27.8%	34.5%	19.5%	25.7%	80.0%	45.7%	24.0%
Semi-detached	33.5%	32.4%	34.7%	34.0%	20.0%	23.9%	35.5%
Terraced/end of terrace	10.3%	9.7%	11.0%	10.7%	0%	8.7%	10.6%
Flat or maisonette	25.5%	22.1%	29.7%	26.5%	0%	19.6%	26.7%
Purpose-built block	20.9%	16.6%	26.3%	21.7%	0%	10.9%	23.0%
Converted house/other	4.6%	5.5%	3.4%	4.7%	0%	8.7%	3.7%
Room (s)	2.7%	0.7%	5.1%	2.8%	0%	2.2%	2.8%
Other	0.4%	0.7%	0%	0.4%	0%	0%	0.5%
Number of residents in household							
One	13.7%	14.5%	12.7%	14.2%	0%	21.7%	12.0%
Two	17.1%	17.9%	16.1%	16.6%	30.0%	34.8%	13.4%
Three	20.2%	19.3%	21.2%	20.9%	0%	13.0%	21.7%
Four or more	49.0%	48.3%	50.0%	48.2%	70.0%	30.4%	53.0%
Ethnicity							
White	74.1%	74.5%	73.7%	73.5%	90.0%	84.8%	71.9%
Hispanic or Latino	0.4%	0.7%	0%	0.4%	0%	0%	0.5%
Black or African American	5.7%	6.2%	5.1%	5.9%	0%	8.7%	5.1%
Native American or American Indian	1.1%	1.4%	0.8%	1.2%	0%	2.2%	0.9%
Asian/Pacific Islander	15.2%	12.4%	18.6%	15.8%	0%	2.2%	18.0%
Other	3.4%	4.8%	1.7%	3.2%	10.0%	2.2%	3.7%
Education							
No schooling completed	10.6%	10.3%	11.0%	10.7%	10.0%	10.9%	10.6%
High school	24.7%	22.1%	28.0%	25.3%	10.0%	21.7%	25.3%
Graduate	37.3%	36.6%	38.1%	37.2%	40.0%	41.3%	36.4%
Post-graduate	24.3%	27.6%	20.3%	24.1%	30.0%	17.4%	25.8%
Other	3.0%	3.4%	2.5%	2.8%	10.0%	8.7%	1.8%
Income							
Very Low	9.1%	5.5%	13.6%	9.1%	10.0%	6.5%	9.7%
Low	17.9%	17.2%	18.6%	18.2%	10.0%	15.2%	18.4%
Average	39.9%	34.5%	46.6%	41.5%	0%	28.3%	42.4%
High	21.7%	26.2%	16.1%	20.9%	40.0%	30.4%	19.8%
Very high	11.4%	16.6%	5.1%	10.3%	40.0%	19.6%	9.7%

4 MODELLING FRAMEWORK AND EMPIRICAL ESTIMATES FOR CHARGING BEHAVIOUR

4.1 Overview

Chapter 4 describes a modelling framework to study the charging behaviour of electric vehicle users, simultaneously with their trip scheduling and parking decisions. The objective of this framework is to explicitly capture drivers' preferences for charging alternatives with the intention to develop a demand-driven smart management of EV recharging.

Charging choices are expressed as a trade-off between the duration of the charging event, the location of the charging station, travel timing and the tariff offered by the charging service provider for the parking/charging bundle. As a result, the underlying decision process has implications for the drivers' scheduling choices and it is affected by their willingness to modify their departure time in order to adapt to the provided services. The focus of the research is out-of-home recharging, which creates the need to capture the interrelation between the marginal utilities for charging attributes as well as for parking attributes.

The context for the stated choices is a smart management system where dynamic pricing is applied in reflection to the systematic variation of time-of-day demand. However, the continuous interaction of supply and demand results in a non-systematic component. The latter depends on the load from the incoming online reservations for the charging "bundles" and on EV drivers' response to variable tariffs. Therefore, the second step of the modelling framework is to identify forward-looking (strategic) behaviour when individuals are presented with objective probabilities for future fluctuations in price.

Chapter 3 presented the survey tool (EV-PLACE) that has been designed in order to collect the data required for the estimation of the charging choice parameters. As it was outlined there, two SP experiments have been conducted: the charging game and the booking game. The primary aim of this chapter is to investigate the decision making of an EV driver, first assuming a differentiated but static time-of-day tariff schedule (estimates from charging game), and then assuming that there are dynamic alterations to this schedule imposed by the charging demand (estimates from booking game).

The specific **objectives** addressed by the charging game in Chapter 4 are the *estimation of parameters* for the charging attributes that are necessary for the choice-based revenue management system suggested in Chapter 6, the improvement of the understanding of charging behaviour by capturing *systematic and random taste heterogeneity* and the *segmentation of EV users* and identification of intra-segment sensitivities as well as willingness-to-pay for certain attributes. This segmentation will define the pricing structure for the charging service provider (CSP).

Similarly, the objectives addressed by the booking game in this chapter are the measurement of drivers' *response to dynamic pricing* for out-of-home charging events, the investigation of their *attitude towards risk* under different model structures and the identification of *strategic behaviour* that could be used for the dynamic interaction between EV drivers and CSPs in future work, as it is described in Chapter 6.

The estimation **results** show that the sensitivity to most of the charging parameters is in agreement with the *a priori* expectations. Socio-demographics and travel attributes partially explain the systematic heterogeneity among the respondents. Also, the drivers can be clearly segmented into two distinctive groups, and this segmentation is possibly affected by attitudinal factors. Finally, when there is uncertainty about future electricity prices the respondents demonstrate a general tendency towards risk-aversion.

Below is the structure of the present chapter:

- Section 4.2 sets the discrete choice modelling background for the charging behaviour analysis. In subsection 4.2.1 there is a description of hybrid choice models and in subsection 4.2.2 we present a summary of time-of-day choice modelling because out-of-home charging preferences are treated simultaneously with time-of-day scheduling preferences in subsection 4.2.3. The latent class framework is presented along with the results from empirical estimates. First, a base MNL specification is applied followed by the enriched specification to account for observed heterogeneity. A diagnostic analysis is performed to correct for scale problems due to the discrepancies between sample recruitment channels. Then mixed logit and latent class formulations are presented to capture unobserved heterogeneity and accomplish the necessary market segmentation. The results from the estimation of the various specifications are interpreted and compared in 4.2.4.

- Section 4.3 underlines the various approaches for risky choices including expected utility theory, rank-dependent expected utility and prospect theory (PT). The attitude towards risk is compared for these approaches and the importance of strategic behaviour both for the dynamic optimisation as well as for the game-theoretical implications for Chapter 6 is highlighted. The empirical results for the response to dynamic pricing are presented in subsection 4.3.4.
- Section 4.4 includes a summary of the empirical findings, emphasising the original contribution of the research and the importance of this chapter for the following analysis.

4.2 Latent class model for joint charging and parking choices

The modelling framework introduced in this section is a modification of a traditional random utility time-of-day choice model, which captures the utility that an EV driver draws from charging his vehicle out-of-home when a charging opportunity is available. The aim of adopting a latent class specification is to identify potential heterogeneity among market segments and to investigate the effect of this segmentation in the revenue management framework for charging service providers that is presented in Chapter 6.

Before proceeding with the presentation of the model and the key results that emerge from the data analysis of the "charging game", a brief review of discrete choice models is presented with a focus on hybrid choice and especially latent class models, existing approaches for activity/travel-timing choices, as well as examples where hybrid choice models have been applied in time-of-day choice modelling frameworks.

4.2.1 Discrete choice models – the use of latent class

In the Discrete Choice Modelling (DCM) theory, an individual has to choose between a set of mutually exclusive alternatives (e.g. car or bus for commuting, type of vehicle to purchase etc.) knowing that he will derive some utility from the chosen alternative. Following the classical microeconomic theory, a rational individual would choose the alternative that would maximise his utility. The alternatives are characterised by a set of attributes (e.g. travel time or travel cost for mode choice) and the utility that the individuals draw from them depends on the value that they place on their attributes. The Random Utility framework becomes necessary in this case because the analyst cannot directly observe an individual's utility (Ben-Akiva and

Lerman, 1985). Therefore, utilities are treated as random variables and the analyst using the random utility model (RUM) theory cannot predict deterministically the choice outcome, but instead, he can predict the choice probability for each alternative.

The general form for the utility that an individual n places to an alternative i in a choice situation s when the choice set is C_{ns} is:

$$U_{nsi} = V_{nsi}(X_{nsi}, Z_n) + \varepsilon_{nsi} \quad \forall\, i \in C_{ns} \tag{4.1}$$

where V_{nsi} is the systematic component of the utility, that is observable by the analyst, and can be described as a combination of the alternative's characteristics X_{nsi} and the characteristics of the decision maker Z_n while ε_{nsi} is the random error component. According to Manski (1973), there are four distinct sources of randomness that could be explained with this term: unobserved attributes, unobserved taste variations, measurement errors and imperfect information or instrumental variables.

Considering all the above, the choice probability for alternative i is equal to the probability that the utility of this alternative U_{nsi} is greater than, or equal, to the utilities of the other alternatives in the choice set C_{ns}, as is shown below:

$$P_{nsi} = \Pr[U_{nsi} \geq U_{nsj,} \quad \forall\, j \in C_{ns}, j \neq i] \tag{4.2}$$

and by substituting U_{nsi} with 4.1:

$$P_{nsi} = \Pr[V_{nsi} + \varepsilon_{nsi} \geq V_{nsj} + \varepsilon_{nsj} \quad \forall\, j \in C_{ns}, j \neq i] \tag{4.3}$$

Afterwards, choice probabilities are derived by assuming a joint probability distribution of the error terms of all the alternatives within the choice set. The specific type of the discrete choice model depends each time on the assumptions made for this distribution.

Typically DCMs are estimated with the maximum likelihood estimation method. The likelihood function to be maximised is equal to:

$$L(\beta) = \prod_{n=1}^{N} \prod_{s=1}^{S_n} \prod_{j \in C_{ns}} P_{nsj}^{y_{nsj}} \tag{4.4}$$

where β is a vector containing the parameters of the model, S_n is the number of choice situations for individual n and y_{nsj} is an indicator which is equal to 1 if individual n has chosen alternative j in choice situation s, and zero otherwise. Instead, it is easier to minimise the negative of the logarithmic transformation of the likelihood function, i.e. the log-likelihood function:

$$LL(\beta) = \sum_{n=1}^{N} \sum_{s=1}^{S_n} \sum_{j \in C_{ns}} y_{nsj} \ln(P_{nsj}) \tag{4.5}$$

A more detailed presentation of the DCM theory can be found in the textbooks by Ben-Akiva and Lerman (1985) and Train (2003).

4.2.1.1 Multinomial Logit model

The most commonly applied DCM in the travel demand modelling literature is the *Multinomial Logit Model (MNL).* The error terms in MNL are assumed to be type I extreme value (Gumbel) independently and identically distributed (IID). The wide adoption of the MNL model from analysts lies on the fact that this distributional assumption leads to a closed form expression for the choice probabilities, which does not require numerical integration or simulation:

$$\Pr(i|X_{nsi}, Z_n, \beta) = \frac{e^{V_{nsi}(X_{nsi}, Z_n, \beta)}}{\sum_{j \in C_{ns}} e^{V_{nsj}(X_{nsi}, Z_n, \beta)}} \tag{4.6}$$

The IID property of the MNL model means that the rate of substitution between any two alternatives in the choice set remains unaffected by any changes or addition of new alternatives in the choice set. The realism of this assumption depends on the existence of correlation between the unobserved components of the utilities of the two alternatives. If correlation exists, any modification in the choice set could have a disproportionate effect in their probabilities.

4.2.1.2 Mixed Logit model

Other models that can accommodate more flexible substitution patterns by relaxing the IID property are the generalised extreme value models (e.g. the nested logit or the cross-nested logit) and the mixed logit model. The *mixed logit* model can take the form of *error component logit* when the error structure is designed so that it allows flexible substitution patterns between the alternatives, or of *random coefficient logit* when the coefficients of the utility function are randomly distributed to capture taste heterogeneity. Regardless the behavioural assumption, the difference of the ML model lies at the functional form of the choice probabilities. Contrary to the MNL model where coefficients are fixed, the logit probabilities of the ML model are integrated over the density *f* of the parameters' probability distribution.

Apart from the set of fixed parameters β now there is also a set of random parameters θ with density $f(\theta)$. Assuming that the IID property holds for the error term and that there is only one choice situation s for each individual, the logit probability for choosing alternative i conditional on parameter θ is:

$$\Pr(i|X_{ni}, Z_n, \beta; \theta) = \frac{e^{V_{ni}(X_{ni}, Z_n, \beta, \theta)}}{\sum_{j \in C_n} e^{V_{nj}(X_{ni}, Z_n, \beta, \theta)}} \tag{4.7}$$

and as a result, the unconditional probability is:

$$\Pr(i|X_{ni}, Z_n, \beta) = \int \Pr(i|X_{ni}, Z_n, \beta; \theta)\, f(\theta) d\theta \tag{4.8}$$

If we assume that the random parameters θ follow a parametric distribution $f(\theta|\omega)$, combining 4.5 and 4.8 the log-likelihood function for the ML model is:

$$LL = \sum_{n=1}^{N} \sum_{j \in C_n} y_{nj} \ln(\int \Pr(i|X_{ni}, Z_n, \beta; \theta)\, f(\theta|\omega) d\theta) \tag{4.9}$$

Since the integral now does not have a closed form as for the MNL model, the choice probability is approximated using simulation methods as below:

$$SP_{nj} = \frac{1}{R} \sum_{r=1}^{R} P_{nj}(\theta = \theta_r) \tag{4.10}$$

where θ_r is a single draw from the parametric distribution out of a total of R draws. Therefore, the simulated probability SP_{nj} is an unbiased estimator of the integral in 4.9. Consequently, the simulated log-likelihood can be generated by replacing SP_{nj} in 4.9. By maximising this function, we can obtain estimates for β and ω where the latter define the shape and scale of the distribution of the parameters θ that vary randomly across the decision makers.

For the purposes of this dissertation and for all stated choice studies, the log-likelihood function needs to accommodate repeated choices by the same individual. Revelt and Train (1998) have developed a framework where the random parameters θ vary across individuals but remain constant across the choice situations faced by a single individual. In this framework, the probability that individual n is observed to make a sequence of choices $I_n = \{i_1, \ldots, i_{S_n}\}$ is:

$$P_{I_n} = \Pr(I_n|X_{ni}, Z_n, \beta) = \int [\prod_{s=1}^{S_n} P_{nsi}] f(\theta|\omega) d\theta \tag{4.11}$$

The simulated probability for the choice sequence I_n is now:

$$SP_{I_n} = \frac{1}{R}\sum_{r=1}^{R}\prod_{s=1}^{S_n} P_{nsi}\,(\theta = \theta_r) \tag{4.12}$$

If $\widetilde{I_n}$ is the sequence of choices for an individual n that is actually observed in the estimation sample and $SP_{\widetilde{I_n}}$ is the simulated probability for this choice sequence, then the simulated log-likelihood takes the following form:

$$\mathrm{SLL} = \sum_{n=1}^{N} ln\, SP_{\widetilde{I_n}} \tag{4.13}$$

where $SP_{\widetilde{I_n}}$ is given by:

$$SP_{\widetilde{I_n}} = \frac{1}{R}\sum_{r=1}^{R}[\prod_{s=1}^{S_n}[\prod_{j\in C_{ns}} P_{nsj}{}^{y_{nsj}}\,(\theta = \theta_r)]] \tag{4.14}$$

and the logit probability is calculated for the chosen alternative by the decision maker n in choice s of the estimation sample and for $\theta = \theta_r$.

The derived simulated log-likelihood is valid when intra-respondent homogeneity is assumed, i.e. when the taste of an individual remains constant from one choice to another. Thus, the random coefficients of the mixed logit model remain constant across choice situations for an individual, which is typically the strategy adopted in stated choice studies, including the analysis following in this subsection. However, Hess and Rose (2009) have questioned this assumption, and they have presented a method that can accommodate intra-respondent heterogeneity for the mixed logit model where the taste of an individual might vary from one choice situation to another.

The flexibility of the ML model has been demonstrated by McFadden and Train (2000) who have indicated that it can approximate any random utility model. In this chapter, mixed logit is used as a mean to capture taste heterogeneity but also for purposes of comparison with the latent class model, which will be described later in detail.

4.2.1.3 Hybrid Choice model

Choice process is a complex research area that has attracted the interest of many disciplines including economists, engineers, psychologists and planners. It has been argued that there is a gap between behavioural theory and predictive choice models (like RUM) because the latter function as "optimising black boxes" that map observed inputs to observed outputs without explicitly treating the cognitive process in-between (Walker, 2001). As a result, there has been a great interest to incorporate latent psychological constructs like attitudes and perceptions into discrete choice models to improve the understanding of an individual's choice process and potentially improve their predictive power (Ben-Akiva et al., 2002a). In this direction, an expanded discrete choice framework has been developed, known as the Hybrid Choice Model (HCM), which is demonstrated in Figure 4.1.

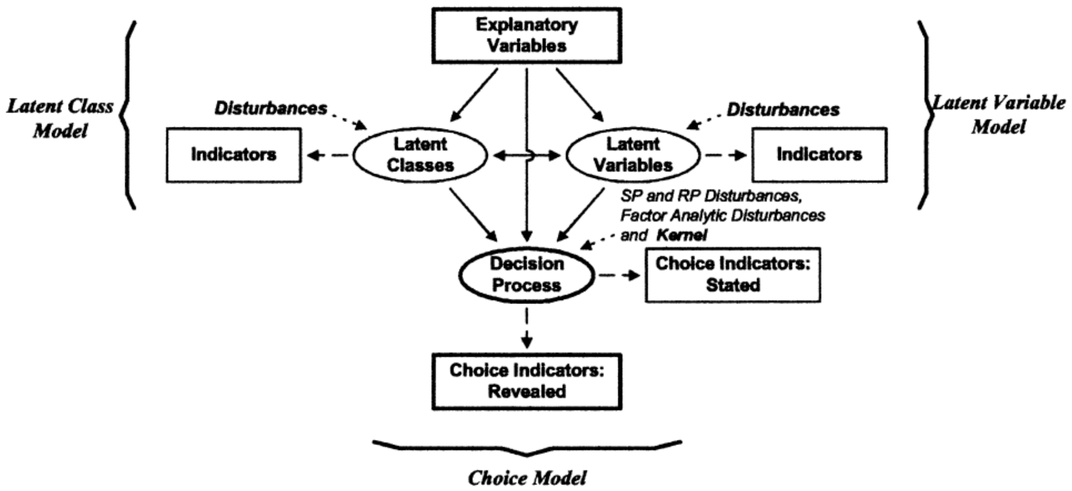


Figure 4.1: The Hybrid Choice Model Framework. Reproduced from (Ben-Akiva et al., 2002a). This image has been reproduced with the permission of the rights holder, Springer.

The main extensions of the HCM framework include (Walker, 2001):

- The addition of heterogeneity by means of flexible covariance structure that relax the IID property (e.g. the random parameters of the mixed logit model).
- The explicit modelling of latent psychological constructs (such as comfort, convenience, satisfaction and perceived costs) that cannot be easily and objectively measured. These *latent variables* are typically measured with the use of psychometric indicators from direct survey questions associated with attitudes and perceptions. Thus, indicators inform the latent variables, which in turn affect the decision process and the utility of the individual for various alternatives.

- The identification of *latent classes* to capture latent segmentation in the market (e.g. different tastes, choice sets or decision protocols).

Hybrid choice models have been applied in the context of electric vehicle or alternative fuel vehicle purchase intentions, in order to capture the effect of perceptions and attitudes on these choices. Some of the latent constructs that have been evaluated in most of these studies are: environmental concerns, transport policies, transport problems, perceived costs, perceived charging characteristics, inclination towards innovation and attitudes towards vehicles features, like design, technology, safety etc. (Jensen et al. 2013; Daziano and Bolduc, 2013; Dimitropoulos, 2014; Daziano and Chiew, 2012; Glerum et al., 2014). Kim et al. (2014) have expanded the scope of this framework by incorporating not only personal attitudinal aspects but also interdependent aspects through social influence variables (e.g. friends, family or colleagues driving an EV) in their HCM. Daziano and Chiew (2012), after a detailed review of vehicle choice models, provide a guideline for data collection along with a list of suggested causal and effect indicators for the latent variable model.

The aim of this dissertation is to estimate class-specific parameters that could inform a charging service provider who is interested in applying tailored services according to the preferences of the EV-user segments. Hence, we are particularly interested in the latent class component of the HCM framework. However, the modelling techniques for the integration of latent variables are presented first, since they will be also required in order to accommodate psychological factors associated with driving and charging an electric vehicle.

Latent variable models are specified and estimated with the use of the structural and measurement equation methodology. *Structural equations* represent a causal relationship while *measurement equations* represent the relationship between the latent variables and the measurable indicators. The Integrated Choice and Latent Variable (ICLV) component of the HCM framework consists of two parts: a discrete choice model and a latent variable model. Each of these parts has, at least, one structural equation and, at least, one measurement equation.

The first element of the framework is the set of **structural equations**. For the latent variable model, we usually have a linear relationship of the latent variables with the characteristics of the individual:

$$X_n^* = \Lambda Z_n + \omega_n \quad and \;\; \omega_n \sim N(0, \Sigma_\omega) \tag{4.15}$$

where X_n^* is the vector of latent variables including latent characteristics of the individual and latent attributes of the alternatives, Z_n are the observable attributes, Λ is the matrix of parameters to be estimated and ω_n are the error components that are typically assumed to follow a normal distribution. The above relationship results in one equation for each latent variable.

Looking at the choice model, the utilities for the alternatives are expressed as a function of the individual characteristics, the observed attributes of the alternatives as well as the unobserved latent constructs:

$$U_{nsi} = V_{nsi}(X_{si}, Z_{n,} X_n^* ; \beta) + \varepsilon_{nsi} \tag{4.16}$$

The choice model can take several forms (e.g. logit, probit, ordinal logit, logit kernel) depending on the assumptions made for the random disturbances ε_{ni}.

Likewise, there are **measurement equations** both for the latent variable model and for the choice model. The measurement equation for the latent variable model expresses the distribution of the indicators (e.g. attitudinal survey questions) conditional on the latent constructs:

$$Y_n = g\big(X_{si}, Z_{n,} X_n^* ; \alpha\big) + v_n \quad and \;\; v_n \sim N(0, \Sigma_v) \tag{4.17}$$

where Y_n is the vector of indicators, g is the functional form (in most studies it is specified as a linear relationship), α is the vector of the parameters to be estimated and v_n are the error components which typically follow a normal distribution. The above relationship results in one equation for each indicator. Sometimes the right-hand side of the equation contains only the latent variables; however, here it is presented with its general form where observable characteristics enter the function as well. For the empirical model in subsection 4.2.4.4, the measurement equation takes the form of ordinal logit because of the ordered structure of the indicators.

For the choice model, the utility is also latent because the analyst cannot directly observe it and the choice outcome is its indicator. Therefore, the measurement equation with the assumption of utility maximisation is:

$$y_{nsi} = \begin{cases} 1, & if \;\; U_{nsi} \geq U_{nsj}, \forall j \in C_n, j \neq i \\ 0, & otherwise \end{cases} \tag{4.18}$$

The unknown parameters can be estimated for the model components using two techniques: a *sequential* approach where the latent variables are first constructed and then enter the choice model as regular variables (Ashok et al., 2002), and a *simultaneous* approach where parameters from the two components are estimated at once (Bolduc and Daziano, 2010). According to Ben-Akiva et al. (2002a), the simultaneous approach should give more efficient estimators but it is used less frequently due to the increased level of complexity. The simultaneous approach implies that there is an expression for the joint likelihood function of the integrated model, which is presented later in this chapter since it relies on the variable forms (e.g. discrete or continuous) and the assumptions about the distributions of the error components.

Apart from the random coefficient mixed logit and the latent variable model, the unobserved heterogeneity in choice situations can be also captured with the use of the **Latent Class (LC)** model (Walker, 2001). LC can be considered a special case of mixed logit where the mixing distribution of the random coefficients is discrete (Train, 2003).

The application of LC models is suitable in cases where there might be discrete segments (or classes) in the sample that exhibit distinct choice behaviour which is not directly identifiable. In essence, they share a lot of similarities with classification methods like cluster analysis, with the main difference that latent class analysis is a model-based approach, thus, it is more flexible for implementation with various data types. The segmentation is made according to a set of characteristics so that individuals within a class have similarities amongst them and dissimilarities with members of other classes. Since it is not possible to define these classes from the observed variables in a deterministic way, class membership probabilities are estimated. The basic formulation of the LC model is:

$$P_n(i|X_i, Z_n, \beta) = \sum_{\kappa=1}^{K} P_n(i|X_i, Z_n, \beta_\kappa; \kappa) P_n(\kappa|z_n) \tag{4.19}$$

where$P_n(i|X_i, Z_n, \beta_\kappa; \kappa)$ is the class-specific probability that might have different specification for the different classes κ, K is the total number of classes, $P_n(\kappa|z_n)$ is the class-membership probability, i.e. the probability of belonging to class κ, conditional on z_n which is the subset of the characteristics of the individual that is used for segmentation. It is inferred that $\sum_{\kappa=1}^{K} P_n(\kappa|z_n) = 1$. Usually, the class-specific probability is formulated as an MNL model; nevertheless, it is possible to adapt the specification for other GEV models, like nested or cross-nested logit (Hess et al., 2009). Unlike the mixed logit, the integral of the choice probability has a closed form and the parameters can be estimated without the use of simulation methods. The advantage of the LC model is that the relationship between the latent classes and the covariates can be evaluated simultaneously with the identification of the classes.

Equation 4.19 can be reformulated for the case of repeated observations, as it is required for the analysis of the choice experiment data later in the chapter. Assuming intra-respondent homogeneity it takes the following form:

$$P_{I_n} = \Pr(I_n|X_i, Z_n, \beta) = \sum_{\kappa=1}^{K} P_n(\kappa|z_n)\,(\prod_{s=1}^{S_n} P_n(i_{n,s}|X_i, Z_n, \beta_\kappa; \kappa)) \tag{4.20}$$

The simplest specification of the LC model arises when the class-membership probabilities are taken as constant across the respondents, i.e. $P_n(\kappa|z_n) = P_\kappa \; \forall n$ and it is commonly called the "finite mixture model". However, flexible segmentation depends on linking these probabilities with individual characteristics of the decision makers. If the class-membership model takes the MNL form then it is given as follows:

$$P_n(\kappa|z_n) = \frac{e^{\delta_\kappa + \gamma_\kappa z_n}}{\sum_{l=1}^{K} e^{\delta_l + \gamma_l z_n}} \tag{4.21}$$

where δ_κ is a class-specific constant and $\gamma_\kappa$is the vector of coefficients for estimation.

LC models have been widely adopted in the travel demand literature especially during the last decade. For electric vehicle adoption, apart from the studies that were mentioned in Chapter 2, latent class approaches were also employed by Bockarjova et al. (2014) and Dimitropoulos (2014). In Dimitropoulos (2014) the class-membership function is defined by a combination of socio-demographic characteristics and environmental attitudes. These attitudes are treated with two different LC specifications. The first one is a Panel Latent Class (PLC) model where the psychometric indicators of environmental concerns enter directly the class-membership function (i.e. transformed values of Likert-scale responses). With this approach, measurement errors or endogeneity between the choice and the level of agreement to Likert-scale questions due to unobserved factors might lead to biased parameter estimations. The second specification, a Hybrid Panel Latent Class (HPLC) model, corrects for these econometric concerns by expressing the psychometric indicators through the underlying latent constructs.

The analysis later in this chapter follows a similar methodological approach to incorporate various attitudes of EV drivers, like pre-planning or parking strategies, into the latent class segmentation. The indicators were clustered to relevant attitudinal groups with the use of factor analysis. Another study in EV choices where this factor analytic technique has been implemented is this of Jensen et al. (2014).

Most importantly, though, the selection of a latent class approach to model charging demand in this study, is based on its segmentation power that has great value for revenue management applications. Calibrating the demand coefficients for different segments of the market (e.g. time-sensitive or price-sensitive users) in RM optimisation problems can increase the accuracy of demand prediction and, hence, improve the revenue performance (Garrow, 2010).

In the airline industry, there are several examples where LC models have been adopted to capture taste heterogeneity for the accommodation of RM systems. Carrier (2008) deviates from the typical deterministic segmentation according to trip purpose and uses other elements from available booking records (distribution channels, travel dates and frequent flyer memberships) to estimate a latent class model, which segments between time-sensitive business users and a mix of leisure and cost-sensitive business users. Teichert et al. (2008) examine the attitudes and the socio-demographics of the travellers within the segments of their LC model and they argue that marketing decisions should be aligned with these characteristics. Wen and Lai (2010) extend the previous specification by incorporating traveller characteristics and trip attributes in the class-membership function and apart from improving the model's predictive accuracy they show that there is a significant differentiation in preferences for service attribute improvements across the user segments. Wen et al. (2013) developed a latent class generalised nested logit model (LCGNL) to identify potential segments of travellers based on their preferences for air and bus carriers. Methodologically, their approach holds the advantages of the LC model and at the same time allows for flexible substitution patterns for the alternatives by relaxing the IID property of the MNL. Drabas and Wu (2013) follow a similar methodology to model air carrier choice by developing the Segment Specific Cross-Nested Logit with Brand-Loyalty (SSCNL-BL) model which can also take into account past choices of the travellers and examine variance in their loyalty.

Market segmentation through LC applications can be also found in other business areas or industries like railway (Hetrakul and Cirillo, 2014), housing (Walker and Li, 2006) or e-commerce (Bhatnagar and Ghose, 2004).

The integration of MNL and LC models within a choice-based revenue management framework, where demand is treated explicitly for pricing and allocation optimisation problems will be further discussed in Chapters 5 and 6.

4.2.2 Time-of-day choice modelling

During the last few decades, transport planners have shown a great interest in understanding and modelling how individuals choose their time of travel and the interrelation of this choice with their daily activities. Identifying the parameters that affect these decisions is very important from a policy perspective because then demand side management strategies could be employed to shift part of the demand to off-peak periods and hence, alleviate congestion. Apart from reducing travel times without significant investment on infrastructure development, these policies are necessary to tackle side effects of traffic congestion, like air pollution with the associated health problems.

The basic concept in this research area is that travellers have a preferred time of travel and any deviation from their schedule will cause some disutility. Vickrey (1969), in his seminal paper on time of travel choices, which focuses on commuting trips, assumes that the final decision for an individual comes after a trade-off between travel time and a measure of early and late arrival to his workplace. In specific, these measures are Schedule Delay Early (SDE) and Schedule Delay Late (SDL) respectively and they can be defined as follows:

$$SDE = \max(PAT - \left(t_d + TT(t_d)\right), 0) \tag{4.22}$$

$$SDL = \max(t_d + TT(t_d) - PAT_b, 0) \tag{4.23}$$

where PAT is the preferred arrival time that can be identified with the official work start time, t_d is the time of departure from home and $TT(t_d)$ is the travel time which depends on the time of departure. The choice is then formulated as a standard microeconomic problem with the maximisation of the following utility function:

$$V(t_d) = \ aTT(t_d) + \beta SDE(t_d) + \gamma SDL(t_d) \tag{4.24}$$

The parameters α, β and γ are assumed to be negative because higher travel times, and arrival times that do not coincide with the preferred arrival times at work, typically cause higher disutility to individuals. Therefore, after trading off the attributes of this utility function, an individual might come up with an optimal choice where he leaves home earlier or later than normally in order to reduce his total travel time.

Small (1982) was the first to transform Vickrey's theoretical microeconomic framework into a discrete choice modelling context and used revealed preference data from commuters in San Francisco to empirically estimate the aforementioned parameters. In his specification, the relationship between schedule delay and disutility is piecewise linear, thus disutility increases linearly both with SDE and SDL. The only difference in Small's utility function is the addition of a "late dummy" to capture jumps in the utility that might arise from potential delays. If θ is the parameter of this lateness penalty then the relationship between the schedule disutility and the arrival time at work can be demonstrated in Figure 4.2. As it can be observed, the coefficient for SDL is expected to be greater in absolute value than the coefficient for SDE, since commuters will typically prefer to arrive earlier than later at work.

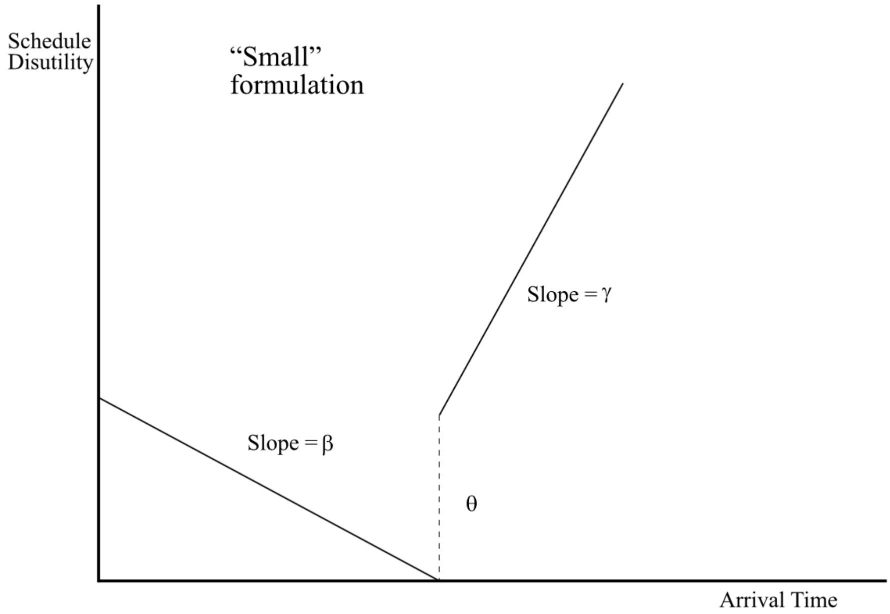


Figure 4.2: Small's formulation for the schedule utility function. Reproduced from (Bates et al., 2001). This image has been reproduced with the permission of the rights holder, Elsevier.

The problem with the models proposed by Vickrey and Small is the absence of an important factor: travel time reliability. Variability in travel times and the uncertainty for the drivers associated with this variability might complicate the pre-planning in order to achieve the preferred arrival time. In this direction, Polak (1987) assumes a probabilistic distribution of travel times for commuters, while Noland and Small (1995) take into account in their expected cost function the time-variation in the predictable component of congestion. The scheduling choice for an individual here is not the time of departure from home t_d, but the amount of time that he would arrive earlier at work T_e if there were no delays related to incidents, which is referred to as "head start" and is dependent on t_d. In particular, T_e is equal to:

$$T_e = PAT - t_d - T_f - T_x \tag{4.25}$$

where T_f is the free flow travel time without congestion and T_x is the "recurrent delay", i.e. the congestion-induced additional time that is anticipated by the individual, which is a deterministic function of the departure time. Travel time TT is the sum of T_f, T_x and a random term T_r. The last term represents "incident delay" and it is not known for sure by the individual because it is caused by non-recurrent congestion. Like with T_x the distribution of T_r is typically dependent on the departure time. With the addition of this random term, the probability of an individual arriving late is based on his subjective estimate of the distribution of T_r. SDE can be now written as $T_e - T_r$ and SDL as $T_r - T_e$ and 4.3 can be reformulated as a problem of choice under uncertainty:

$$E[V(t_d)] = \alpha E[TT(t_d)] + \beta E[SDE(t_d)] + \gamma E[SDL(t_d)] \tag{4.26}$$

Applying the Maximum Expected Utility (MEU) framework, which will be discussed thoroughly in section 4.3, the optimal departure time t_d^* is the value which maximises $E[V(t_d)]$ and:

$$E[V(t_d)] = \int_0^\infty V(t_d) f(T_r) dT_r \tag{4.27}$$

where the expectation operator E[•] is based on the individual's subjective assessment of the probability distribution $f(T_r)$.

Detailed reviews of studies that have explicitly treated travel time variability in scheduling decisions can be found in Bates et al. (2001) and in Noland and Polak (2002).

The approaches described above were addressed to the departure time choice of morning commuters who travel to work by car. Nevertheless, the same framework could be adapted to cover a more generic journey context. An additional implication by changing the time of departure is travel cost (time-of-use road pricing or peak-period prices for public transport) and there are several studies that examined this problem in conjunction with road pricing schemes (for example, Polak and Jones, 1994 and Arellana et al., 2013).

An alternative approach to the traditional trip-based framework for departure time choice modelling was introduced by Polak and Jones (1994). Their tour-based specification allows the simultaneous modelling of the time-of-day choice for the inbound and the outbound leg of a home-based tour. Also, it has the advantage of linking the travel decision with the intrinsic preferences of the individual for activity time participation. More recently, this general methodology has been adopted and extended with the use of error components by de Jong et al. (2003) in their empirical application.

In order to estimate time-of-day choice models, past studies have employed RP data (Small, 1982), SP data (Ettema et al., 2004), as well as combination of the two (Arellana et al., 2013).

Moreover, in most of the cases, schedule delays were not calculated based on the PAT but based on observed arrival times. The reason for this approach is that in order to elicit the preference for arrival time at work or other activities, this question needs to be explicitly asked in the survey tool. The argument in using observed timings ("the current position" or "the status quo") as reference points is that the estimated coefficients are not consistent with Small's specification unless we assume that the actual observations coincide with the preferred times.

The joint parking and charging choice modelling framework that is presented in this chapter is characterised by scheduling decisions since the time preferences for the charging events will have a direct effect on travel timings. To the authors' knowledge, the only studies that have considered the effect of latent attitudes in scheduling choices are those of Arellana et al. (2013) and Thorhauge et al. (2014). In a much more similar context to this dissertation, Daina (2014) has developed an ICLV model to explain the joint charging and activity-timing choices of electric vehicle drivers. One of the main novelties of the framework presented here is the consideration of parking choices and the effect of drivers' perceptions and attributes on planning a charging event for an out-of-home location.

4.2.3 Modelling framework

In order to jointly analyse the parking and charging choices within an activity-based framework, out-of-home charging preferences are simultaneously treated with time-of-day scheduling preferences. The interrelated dimensions of the choice framework are presented in Figure 4.3. The four attributes of the choice experiment are highlighted in bold. For example, it can be observed that charging duration is influential for all choice dimensions while price affects only parking and charging choices. This graph also contains additional attributes (e.g. charging location or activity duration) that have potential indirect implications for the final choice. For example, an individual who changes his departure time from home in order to obtain a cheaper charging service in a shopping location may alter his activity duration at the destination, as a by-product of his charging choice. The understanding of these interrelated dimensions is crucial from the perspective of a charging service provider, in order to apply pricing mechanisms that would shift charging events from peak to off-peak load periods.

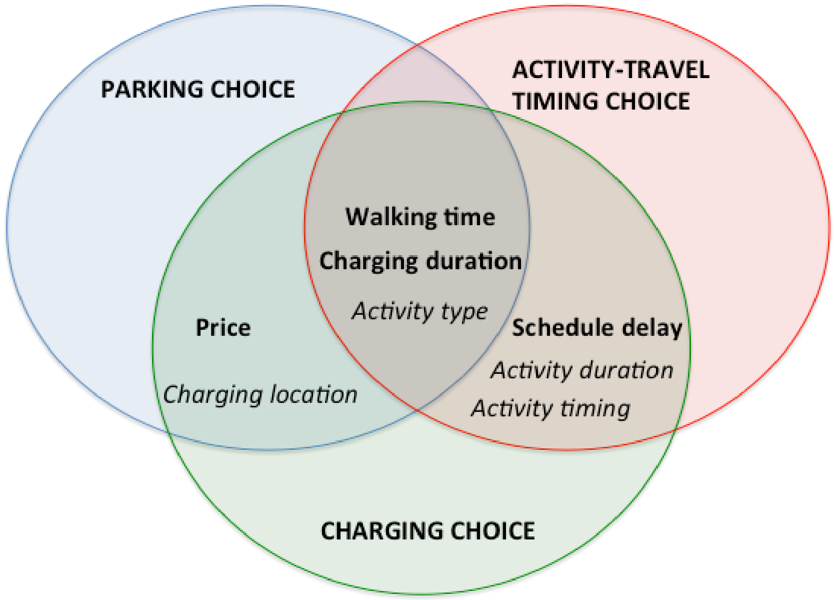


Figure 4.3: Relations between the three choice dimensions: parking, charging and activity travel-timing

The main *assumptions* that we make are the following:

- EV drivers are informed about available charging opportunities and they make their decisions before they leave home for their daily tour.
- The starting time of their preferred charging event affects the arrival time at their destination and consequently the departure time from home.
- Charging alternatives are evaluated and compared by the individual, based on four attributes: combined price of charging and parking, walking time to the destination, charging duration and starting time of the charging event.
- The energy that is required in order to complete the daily schedule and return at home is not adequate without recharging the vehicle in-between.
- There is always only one charging opportunity even if the individual's daily tour contains more than one activity stops.
- The parking duration is exogenously defined by the duration of the respective activity and the charging duration is always less or equal to the parking duration.
- The energy amount of the charging option (and hence the energy available after charging) is also exogenous, and it is defined by the charging service provider. Moreover, it is constant across choice situations for an individual.

Starting by the last point, energy quantity is a continuous variable and discretizing it in order to treat it as an attribute for the choice experiment would lead to loss of information. Ideally, this would require a discrete/continuous modelling approach so that the charging-parking option choice and the quantity choice are treated simultaneously. Nevertheless, since the price of the parking/charging option depends on the quantity demanded in a non-linear way, due to the dynamic character of electricity price, complex endogeneity issues would arise.

The discrete-continuous analysis lies beyond the scope of the present thesis because the developed choice model should be integrated with the revenue management component in Chapter 6, and the foundation of RM applications is the comparison of products with identical quantities (i.e. preference of one airline seat over another). Hence, the assumption here is that the choice of the EV driver is based on a sequential process: first, he requests a certain amount of energy from a charging service provider for his preferred parking interval, and if the delivery of this amount is feasible within the given time, he is provided with a set of charging options that could satisfy his requirements. Our focus is to understand the second step of this sequential process, i.e. to estimate the relative values of the charging service attributes, while the first step is assimilated into the scenario description of the choice experiment. The identification of energy quantity preferences with a discrete/continuous framework is an interesting topic for future research outside the RM context.

After the individual has stated his preferred energy quantity, the charging service provider evaluates the possible charging options that could cover his needs and this entails alternatives with different charging rates, and thus, charging durations. Charging duration is assumed to be constrained by parking duration and activity scheduling; yet, the starting time of the chosen charging option might be earlier than the preferred arrival time if there are price-sensitive drivers that are willing to alter their schedule in order to get a discounted offer.

Since charging duration is less than or equal to the parking duration, early arrival and late departure from the activity place cannot be assessed at the same time. The starting time of a charging option in the choice experiment either precedes the starting time of the associated activity or it coincides with it. This allows the estimation of what we call the Charging Induced Schedule Delay Early (CISDE). A late departure would correspond to a Charging Induced Schedule Delay Late (CISDL) for the next activity of the daily chain, which is not estimated here, but is calculated based on the SDL/SDE ratio for the RM application[34]. The CISDL for the examined activity is always equal to zero as it is assumed that the charging process can be initiated any time after the vehicle has been plugged into the grid. As a result, the individual

[34] The CISDE and CISDL terms are also used in Daina (2014) but their conceptual meaning is slightly different in our framework due to basic dissimilarities in the way that charging episodes are defined.

does not need to deviate from his preferred arrival time. For clarification, the scheduling terms of a hypothetical tour[35] with two activities are visually demonstrated in Figure 4.4.

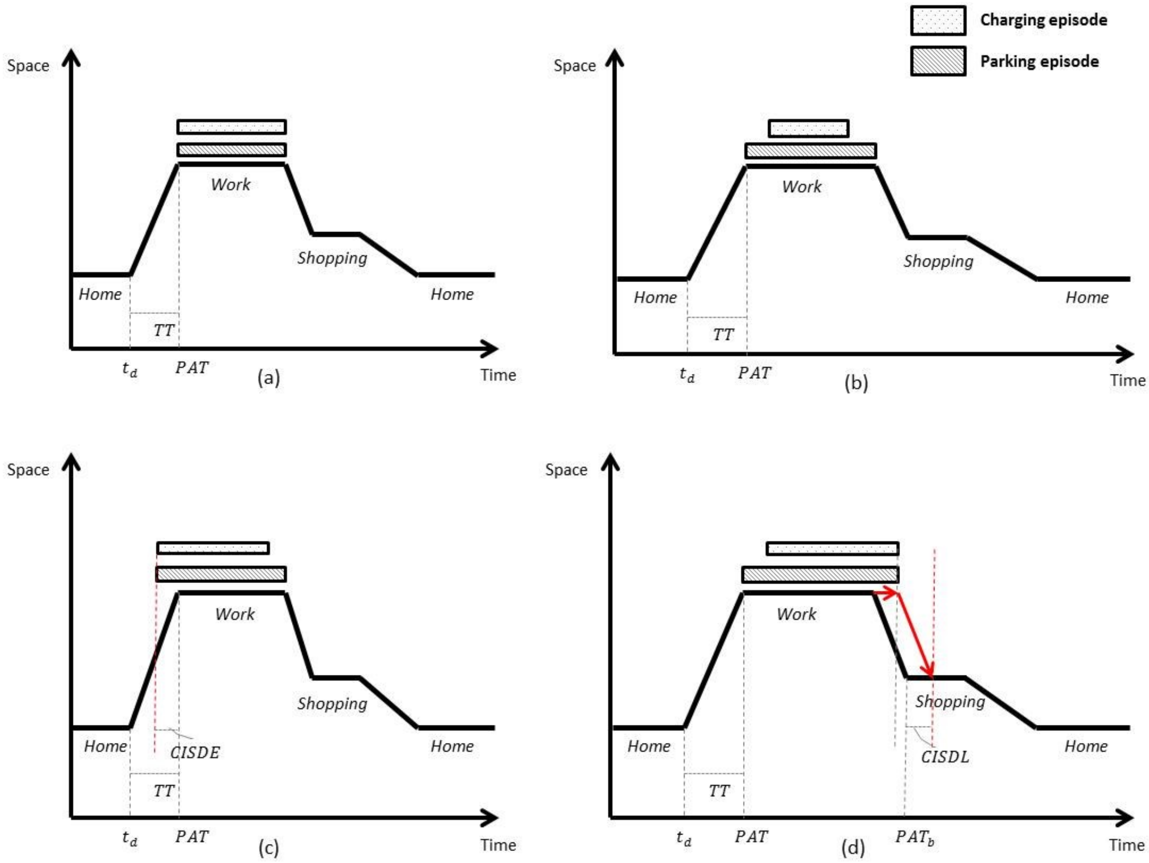


Figure 4.4: The effect of the joint parking and charging choice on scheduling disutility for four scenarios: a) the charging episode coincides with the parking episode – no scheduling disutility, b) the charging episode is contained within the parking episode – no scheduling disutility, c) the charging episode and hence the parking episode starts before the PAT causing a CISDE and d) the charging episode and hence the parking episode finishes after the preferred departure time causing a CISDL for the subsequent activity

The necessity of choosing one of the available charging options due to range concerns is restrictive since it is excluding the "opt-out and charge at home" option. Moreover, the single-day decision frame renders the choice to be somewhat myopic since some drivers charge their vehicles less frequently and might consider next day's schedule and charging opportunities before they select to pay for an out-of-home charging option. Finally, the low battery assumption at the beginning of the day potentially exaggerates reality for the majority of current EV owners who have the ability to charge at home and do not regularly face such stressing range conditions.

[35] The tour-based schematic here is used for demonstration purposes. The estimation is based on a trip-based approach since the choice experiment contains only scenarios similar to a, b and c that do not strictly affect the timing of the subsequent activity.

The above leads, undoubtedly, to a simplification of the actual problem. However, the *benefit* from this simplification is that it allows the modelling of some hitherto unrevealed, aspects of charging behaviour. Specifically:

- The consideration in the choice process of a whole set of charging options, with electricity prices varying across time and space and decision makers being well-informed for these variations
- Since the preferences are stated and not revealed, they are not necessarily representative of present exogenous factors, like energy prices and power network utilisation. The idea is that DSM techniques after a significant penetration of EVs in the market could considerably change the context under which individuals choose to charge their vehicles. With dynamic pricing, out-of-home charging prices could become competitive to home energy tariffs especially if they are marketed as "bundles" with other parking privileges by parking operators or charging service providers. Therefore, the exclusion of "home charging" as an opt-out from the charging choice should prevent the situation where a great share of EV drivers resorts to this option due to its intimacy to their status quo behaviour. In this way, it is possible to examine the marginal utility they would gain from combined parking-charging attributes and estimate parameters that could have great prediction value for future scenarios with increased energy prices and the introduction of new business models for electro-mobility. Besides, as Veldwijk et al. (2014) stated, "If individual preferences are measured to determine which components define the most preferred program or treatment, the inclusion of an opt-out option might not be a necessity but rather a threat to efficiency".
- Along similar lines, it is likely that a substantial portion of future EV drivers in large urban centres won't have access to off-street parking (i.e. charging opportunity) at home. In this case, the low battery assumption will be much more relevant for the decision maker. If it is presumed that the estimated behaviour is transferrable to people with similar demographic characteristics (e.g. income, age etc.) that only differ in their lack of parking availability, then our model can gain significant predictive power for various scenarios of future EV adopters.

After presenting the limitations and the opportunities of the modelling framework, the total utility of the joint charging and parking choice can be expressed as a sum of two sub-terms:

the utility related to the joint parking and charging option and the utility related to the activity/travel episode:

$$U_i = U_i^{charging-parking\ option} + U_i^{activity-travel\ episode} \tag{4.28}$$

where i refers to a specific combination of charging and activity/travel-timing option.

The systematic part of the utility related to the joint parking and charging option depends on three out of the four attributes that characterise a charging alternative: the combined price of parking and electricity, the walking time from the parking location to the activity destination and the duration of the charging event. Theoretically, charging duration should not have a significant effect on the final choice of the decision maker since the energy quantity delivered at the end of the charging episode is the same across the alternatives. Therefore, the CISDE/CISDL disutility is caused by the starting time of the charging episode and not by its duration. Nevertheless, EV drivers might have implicit preferences for shorter or longer charging episodes. For example, longer charging episodes might be perceived as reducing the "availability window" of the vehicle during the parking episode and thus the option value of leaving earlier than the preferred departure time due to an unexpected event (Daina, 2014). The expression for the systematic utility of the joint parking and charging choice is linear-in-attributes:

$$V_i^{charging-parking\ option} = \beta_{CP}CP_i + \beta_{WT}WT_i + \beta_{CD}CD_i \tag{4.29}$$

where CP_i is the combined price, WT_i is the walking time, CD_i is the charging duration and β_{CP}, β_{WT}, β_{CD} are the parameters to be estimated.

The systematic component of the utility from activity/travel timing can be derived from equation 4.24 after excluding SDL (and any associated late penalties) which was not evaluated in the choice experiment and TT, assuming that the contribution of the travel time to the total disutility is trivial compared to the disutility induced from a shifted charging episode:

$$V_i^{activity-travel\ episode}(t_{0,i}) = \beta_{CISDE}CISDE(t_{0,i}) \tag{4.30}$$

where $t_{0,i}$ is the starting time of the charging episode of option i and $CISDE(t_{0,i})$ is derived from equation 4.22 as follows:

$$CISDE(t_{0,i}) = \max(PAT - t_{0,i}, 0) \tag{4.31}$$

Combining the two systematic components (equations 4.29 and 4.30), the utility that an individual n gains from choosing alternative i can be expressed as:

$$U_{in} = \beta_{CP}CP_{in} + \beta_{WT}WT_{in} + \beta_{CD}CD_{in} + \beta_{CISDE}CISDE(t_{0,in}) + \varepsilon_{in} \tag{4.32}$$

where ε_{in} is the iid extreme value error term. The subscript n is added here to capture the variability in driving patterns and the idiosyncratic preferences of the EV drivers. The parameters of 4.32 are estimated in the following subsection.

4.2.4 Empirical estimation

For the charging game of the EV-PLACE survey, as it was presented in Chapter 3, respondents had to choose between two charging alternatives according to the activities and the timings of the home-based tour that they have selected earlier. In the choice cards, they were able to identify where the charging opportunity was located, amongst the activity stops of their tour. Figure 4.5 shows an example of a choice situation for a home-work daily tour where the four charging attributes discussed earlier are highlighted for the two alternatives. These indications were also projected to the respondents during the instructional video so that they are able to distinguish the "variables" from the remaining information (right part of the screen), which is the constant scenario across the choice situations.

Considering the fact that there are repeated observations from the stated preference tool, the utility function of equation 4.32 becomes:

$$U_{ins} = ASC_i + \beta_{CP}CP_{ins} + \beta_{WT}WT_{ins} + \beta_{CD}CD_{ins} + \beta_{CISDE}CISDE(t_{0,ins}) + \varepsilon_{ins} \tag{4.33}$$

where s is the choice situation and ASC_i is the alternative specific constant of option i. For unlabelled choice experiments, like the current one ASC_i can only capture the effect of the alternative's position on the screen.

4.2.4.1 MNL base specification

Assuming that the IIA property holds for the error term ε_{in}, the choice probabilities are given by the MNL model (equation 4.6), which for the joint charging and parking choice takes the following form:

$$P_{in} = \frac{e^{\beta_{CP}CP_{in} + \beta_{WT}WT_{in} + \beta_{CD}CD_{in} + \beta_{CISDE}CISDE(t_{0,in})}}{\sum_{j \in C_n} e^{\beta_{CP}CP_{jn} + \beta_{WT}WT_{jn} + \beta_{CD}CD_{jn} + \beta_{CISDE}CISDE(t_{0,jn})}} \tag{4.34}$$

where C_n is the choice set for individual n. The limitation of the IIA property in the present context lies in the fact that the substitution rates between alternatives are the same, regardless if their attributes (e.g. charging duration, walking times) have adjacent values or not. For example, if a higher tariff is introduced in a facility located half a mile from the destination to discourage drivers from plugging-in their EVs there, this will cause a proportionate increase in the choice probability of a charging post 2 miles away and a charging post 5 miles away from the destination. The reasonable expectation is that the drivers will disproportionally choose to move to the closest available charging post, i.e. the one located in a 2 miles distance.

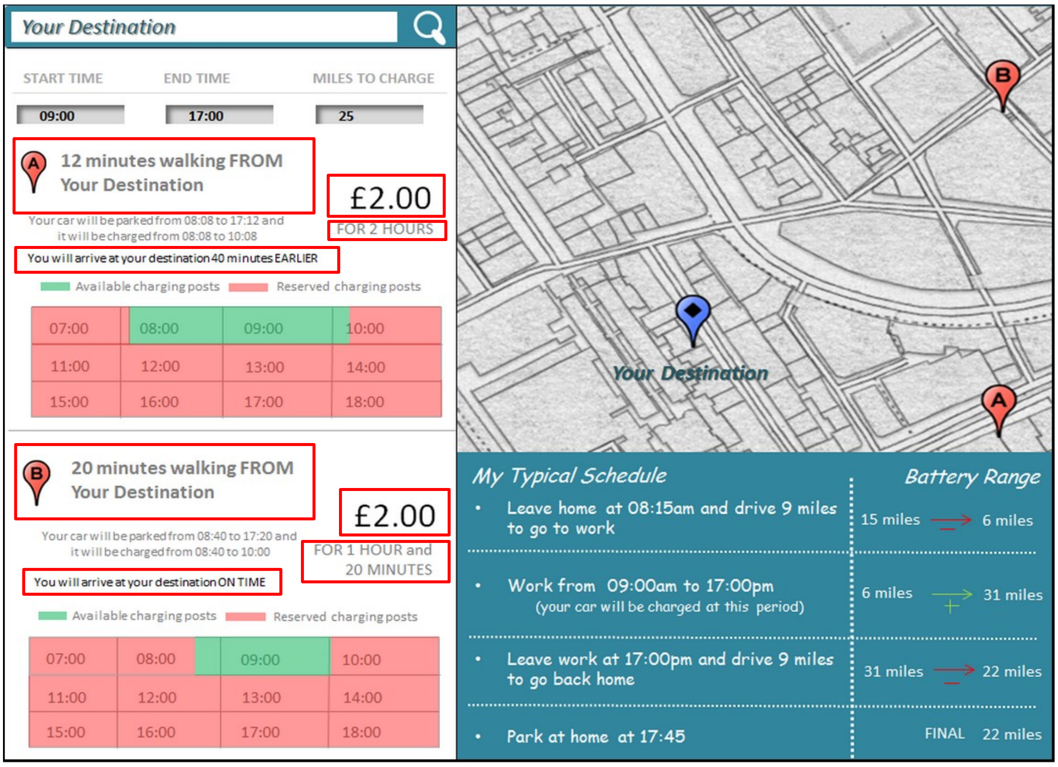


Figure 4.5: Example of a choice situation from the charging game

The MNL might be limiting in this perspective, yet it is very useful for a preliminary estimation of the sample to gain insights into the significance, the signs and the relative magnitude of the charging parameters. Flexible substitution patterns and taste heterogeneity are introduced later with more advanced specifications.

The MNL estimates from the base specification of 4.33 are presented in Table 4.1. The overall fit of the model is indicated by the likelihood ratio index $\boldsymbol{\rho}$[36]. All the estimated parameters are statistically significant. The parameters for price, walking time and CISDE have the expected negative sign while the parameter for charging duration is positive, suggesting an implicit

[36] The likelihood ratio index $\boldsymbol{\rho}$ is a statistic that measures the goodness-of-fit of a model. It is defined as $\rho = 1 - \frac{LL(\beta)}{LL(0)}$, where $LL(\beta)$ is the final log-likelihood, i.e. the log-likelihood calculated with the estimated parameters β after convergence, and $LL(0)$ is the null log-likelihood, which is calculated for all parameters set to zero. For linear-in-parameters specifications, this statistic measures how well the model performs compared to a model assigning equal probabilities to all alternatives. The adjusted likelihood ratio $\overline{\boldsymbol{\rho}}$ index is defined as $\overline{\boldsymbol{\rho}} = 1 - \frac{LL(\beta) - K}{LL(0)}$, where K is the number of estimated parameters, and it penalizes less parsimonious specifications.

preference for longer charging durations. The sign of the charging duration parameter is discussed in more detail later but it is noted at this point that it could be attributed to endogeneity as a result of measurement error. Finally, the ASC for option A is positive and statistically significant, indicating that the respondents tend to choose the alternative that is located on the top part of the reservation screen.

Table 4.1: MNL charging choice, “charging game” – base model specification

Variables		Coefficient	Std error	t-test	p-value
ASCA		0.187	0.0677	2.77	0.01**
ASCB		0	fixed	***	***
CP [£]		-0.571	0.0593	-9.63	0.00**
WT [mins]		-0.0408	0.0065	-6.27	0.00**
CD [mins]		0.0031	0.0013	2.42	0.02**
CISDE(t_0)[mins]		-0.0143	0.0231	-6.19	0.00**
Number of estimated parameters	5				
Number of individuals	118				
Number of observations	1062				
Null log-likelihood	-736.122				
Final log-likelihood	-646.699				
Likelihood ratio index $\boldsymbol{\rho}$	0.121				
Adjusted likelihood ratio index $\bar{\boldsymbol{\rho}}$	0.115				

Two asterisks (**) indicate that the coefficient for this parameter is statistically significant at the p<0.05 level while one asterisk (*) indicates that the coefficient is statistically significant at the p<0.10 level.

In Chapter 3, it was shown that 263 respondents completed the EV-PLACE survey. However, taking into account that the instructional video for the charging game lasted three minutes, all individuals that completed the exercise in less than four minutes were not further processed, since it would be difficult to argue that they made actual trade-offs between the charging alternatives. As a result, the final sample size consists of 118 individuals and, considering that each of them responded to nine choice situations, they correspond to 1062 observations. Examining if there are systematic patterns among the respondents that were excluded from the analysis, it was observed that the proportion of young, employed and individuals that live in London is slightly increased compared to the initial sample.

One significant characteristic of the survey sample is that it consists of both EV drivers and people that do not have experience with driving an EV (although they have considered buying one during the last 12 months). The charging preferences are expected to have dissimilarities between the two groups and hence the sample is split in order to identify them. For the full specification, later, a dummy variable for owning/leasing an EV is interacted with the charging attributes in order to capture its effect. The estimated parameters for the two sub-samples are presented in Table 4.2.

The goodness-of-fit for the "EV drivers" model is higher than the goodness-of-fit for the "EV considerers" model, indicating a larger variability across individuals in the utility parameters for the latter. The parameters have the same sign and similar values as above, yet the charging duration is not statistically significant for the "EV considerers" group. It is also observed that EV drivers have a higher sensitivity to price and time of arrival while EV considerers are slightly more sensitive to walking time.

Table 4.2: MNL charging choice, "charging game" – sample split among EV drivers and EV considerers

	EV drivers				EV considerers			
Variables	Coefficient	Std error	t-test	p-value	Coefficient	Std error	t-test	p-value
ASCA	0.173	0.0920	1.88	0.06**	0.212	0.101	2.09	0.04**
ASCB	0	fixed	***	***	0	fixed	***	***
CP [£]	-0.639	0.0804	-7.95	0.00**	-0.491	0.866	-5.55	0.00**
WT [mins]	-0.0389	0.0089	-4.39	0.00**	-0.0445	0.0098	-4.57	0.00**
CD [mins]	0.0047	0.0018	2.68	0.01**	0.0013	0.0019	0.67	0.51
CISDE(t_0)[mins]	-0.0196	0.0032	-6.12	0.00**	-0.0080	0.0034	-2.33	0.02**
Number of estimated parameters	5				5			
Number of individuals	68				50			
Number of observations	612				450			
Null log-likelihood	-424.206				-311.916			
Final log-likelihood	-358.569				-283.347			
Likelihood ratio index ρ	0.155				0.092			
Adjusted likelihood ratio index $\bar{\rho}$	0.143				0.076			

Taking into account the different recruitment channels, it can be assumed that the sample consists of multiple data sources and hence it is important to check for taste homogeneity and variance differences among them. For this reason, the MNL model is estimated separately for the respondents that have been recruited by the researchers and for those that have been recruited by Panelbase.com. The results are presented in Table 4.3.

It can be seen that there is a significant difference in the goodness-of-fit for the two data sources, suggesting a higher degree of error associated with the Panelbase respondents. The estimated parameters have the same sign, but they are of different scale while the main inconsistency is the statistical significance of the alternative specific constant for Option A.

Table 4.3: MNL charging choice, "charging game" – sample split among different recruitment channels

	Internal recruitment				**Panelbase**			
Variables	Coefficient	Std error	t-test	p-value	Coefficient	Std error	t-test	p-value
ASC_A	0.0193	0.141	0.14	0.89	0.253	0.079	3.20	0.00**
ASCB	0	fixed	***	***	0	fixed	***	***
CP [£]	-0.854	0.127	-6.73	0.00**	-0.481	0.685	-7.02	0.00**
WT [mins]	-0.0664	0.0142	-4.69	0.00**	-0.0342	0.0076	-4.48	0.00**
CD [mins]	0.0043	0.0029	1.50	0.13	0.0034	0.0015	2.32	0.02**
CISDE(t_0)[mins]	-0.033	0.0052	-6.35	0.00**	-0.0078	0.0027	-2.91	0.00**
Number of estimated parameters	5				5			
Number of individuals	37				81			
Number of observations	333				729			
Null log-likelihood	-230.818				-505.304			
Final log-likelihood	-170.327				-460.619			
Likelihood ratio index $\boldsymbol{\rho}$	0.262				0.088			
Adjusted likelihood ratio index $\bar{\boldsymbol{\rho}}$	0.240				0.079			

Hensher et al. (1998) suggest that if the parameter vector of one model is plotted against the parameter vector of the other model and the graph exhibits a positive, proportional relationship between the two then the hypothesis for equal taste parameters and unequal variances should hold. The ratio of variances, in this case, is equal to the slope of the underlying curve. Figure 4.6 illustrates this plot and reveals that the expected relationship holds for all parameters apart from the alternative specific constant for option A, which is of greater relative importance for Panelbase respondents than for the rest of the sample. This visual test is similar to a t-test of the difference between the estimates; however, it is useful in this case to demonstrate that the ASC_A is an outlier.

In order to combine the observations from the two sub-samples, considering the increased variance of the error term for Panelbase, it has been decided to take account of the difference in scale of their corresponding utilities. This is achieved by estimating a scale parameter that is multiplied with the utility of the Panelbase sub-sample. The effect of this scale parameter is that the utility of this dataset is forced to have the same scale with the utility of the other respondents. Here, the internally recruited sub-sample was set as the reference environment since it can be considered to reflect a more realistic behaviour and the scale factor was fixed as equal to one. The main reason for this assumption is that it includes only EV drivers, who should be more familiar with the hypothetical situations. The MNL model with the additional scale parameter is presented in Table 4.4. The results show that the scale parameter is significant, and after its inclusion, the goodness-of-fit for the base specification has improved.

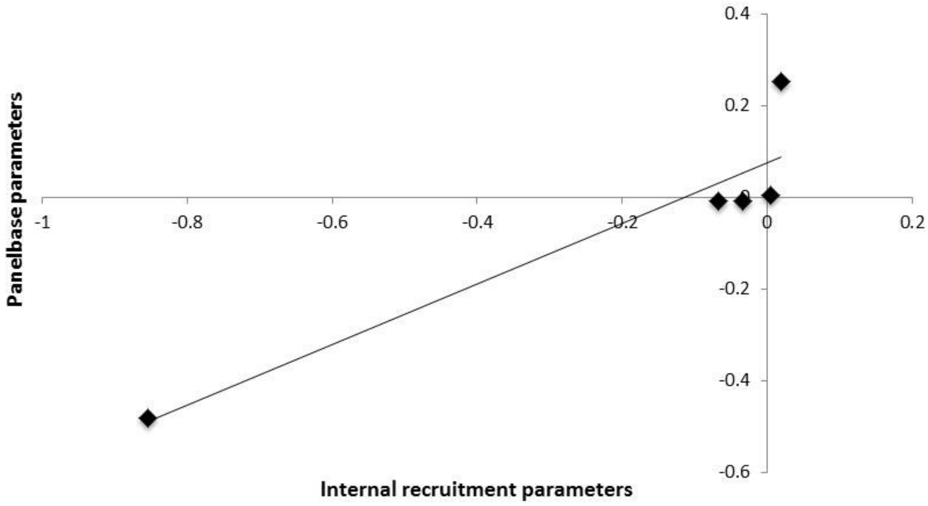


Figure 4.6: Plot of MNL attribute coefficients for different recruitment channels

Table 4.4: MNL charging choice, "charging game" – accounting for scale differences

Variables		Coefficient	Std error	t-test	p-value
ASCA		0.217	0.107	2.04	0.04**
ASCB		0	fixed	***	***
CP [£]		-0.918	0.120	-7.66	0.00**
WT [mins]		-0.0666	0.0118	-5.65	0.00**
CD [mins]		0.0046	0.0021	2.22	0.03**
CISDE(t_0)[mins]		-0.0269	0.0048	5.66	0.00**
Scale for recruitment channel (η)		0.469	0.0829	5.66	0.00**
Number of estimated parameters	6				
Number of individuals	118				
Number of observations	1062				
Null log-likelihood	-736.122				
Final log-likelihood	-637.989				
Likelihood ratio index ρ	0.133				
Adjusted likelihood ratio index $\bar{\rho}$	0.125				

4.2.4.2 MNL with interaction terms

For the choice experiment above, it is difficult to make *a priori* assumptions regarding the socio-demographics and other trip characteristics and their effect on charging attributes. Nevertheless, capturing systematic heterogeneity with their inclusion in the model increases the predictive power of the model, when information is available about the forecasted population. Since the individuals' characteristics are invariant across choice alternatives, it is not easy to examine this heterogeneity. However, by interacting them with the varying charging attributes it is possible to relax this limitation.

Individual characteristics, scenario-based trip attributes, current charging preferences of EV drivers and other factors that are interacted with the four charging attributes of the base specification are the following[37]:

- Gender (**Female**, Male)
- Age group (**Less than 39**, Over 39)
- Employment status (**Employed,** Student, Retired, Unemployed, Unable to work)
- Having children (**Yes**, No)
- Marital Status (**Married or domestic partnership,** Single/Never Married, Widowed, Divorced, Separated)
- Living alone (**Yes**, No)
- Ethnicity (**White,** Hispanic/Latino, Black African/American, Native American/Indian, Asian/Pacific Islander, Other ethnicity)
- Education (**University graduate,** No schooling, High school, Other education)
- Income[38] (**Very high,** High, Average, Low, Very Low)
- Electric vehicle access – Owning or leasing an EV (**Yes**, No)
- Day of travel (**Weekday,** Weekend)
- Number of daily activities in the trip chain

[37] Values in bold enter the full specification while the other values in the respective category are fixed as reference. Among these variables, we tested the performance of other consumer characteristics, like their residence location, the type of accommodation, the availability of a conventional ICE vehicle, the frequency of driving their EV, the typical daily distance with their EV, their safety battery "buffer" and their recharging frequency, as well as trip-related scenario variables like the energy amount of the charging event, the remaining SOC at the end of the day and the parking duration. However, none of these variables influence the results presented later.

[38] It is considered that UK respondents belong to the very high income band for a net annual income after tax greater than £70,000, while for the Irish respondents the threshold is 70,000 €.

- Number of profile searches[39]
- Work-based tour (**Yes,** No)
- Driving distance before charging (in miles)
- Driving distance after charging (in miles)
- Initial SOC – before the charging event (range in miles)
- EV Loyal enthusiasts[40] (**Yes**, No, Non-EV drivers)
- EV driving experience (**Driving the EV more than one year,** Driving the EV less than one year, Non-EV drivers)
- Longest distance driven between charging events (**Less than 20 miles,** More than 20 miles, Non-EV drivers)
- Current daily cost of recharging (**Free,** Less than 50p, 50p - £1, £1 - £2, £2 - £4, More than £4, Non-EV drivers)
- Currently charging out-of-home – at work, at shopping, on-street or other locations (**Yes,** No, Non-EV drivers)

The final specification, accounting for systematic taste variations, was obtained by sequentially adding interaction terms and keeping those that were found to be significant with an 80% level of confidence. As more confounding terms entered the utility function the significance of some variables decreased significantly, and thus, they were removed from the final specification. The estimated parameters are presented in Table 4.5. It can be seen that the goodness-of-fit has increased compared to the base specification ($\bar{\rho}$ is 0.160 vs 0.125).

The results show that there are several attributes that explain the variability in the marginal utilities for the charging attributes. Below there is an exploration of the estimates that were found to be statistically significant.

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[39] As it was described in Chapter 3, the respondents could choose one of the travel profiles presented to them initially, or search in other pages until they find a representative profile.

[40] Based on the Net Promoter Score (NPS), which is a management tool to measure customer satisfaction (https://en.wikipedia.org/wiki/Net_Promoter), we characterize the electric vehicle drivers that respond to the question "From a scale of 1 to 10, how likely is that you would recommend your EV to a friend or colleague?" with a score of 9 or 10, as EV loyal enthusiasts.

Table 4.5: MNL charging choice, “charging game” – final specification with interaction terms

Variables	Coefficient	Std error	t-test	p-value
ASCA	0.226	0.137	1.65	0.10*
ASCB	0	fixed	***	***
CP [£]	-3.080	0.852	-3.61	0.00**
CP * Age <39 [£]	0.567	0.270	2.10	0.04**
CP * Having Children [£]	0.326	0.264	1.23	0.22
CP * Employed [£]	-0.813	0.384	-2.12	0.03**
CP * EV Loyal Enthusiasts [£]	0.803	0.301	2.67	0.01**
CP * Longest distance driven between charging events < 20 miles [£]	-1.27	0.644	-1.98	0.05**
CP * Work Based Tour [£]	0.657	0.363	1.81	0.07*
CP * Initial State of Charge [£ * miles]	0.222	0.160	1.39	0.16
WT [mins]	-0.323	0.0679	-4.76	0.00**
WT * Married or Domestic partnership [mins]	0.0928	0.0422	2.20	0.03**
WT * Living alone [mins]	0.0821	0.0478	1.72	0.09*
WT * Free EV charging [mins]	0.0955	0.0683	1.40	0.16
WT * Charging out-of-home [mins]	0.0516	0.0284	1.82	0.07*
WT * Weekday travel [mins]	0.0485	0.0313	1.55	0.12
WT * Number of daily activities [mins]	0.0305	0.0207	1.48	0.14
CD [mins]	0.00476	0.0152	3.13	0.00**
CD * Female [mins]	0.0063	0.0077	0.82	0.41
CD * Employed [mins]	0.0068	0.0033	2.11	0.03**
CD * Ethnicity – White [mins]	-0.0230	0.0107	-2.16	0.03**
CD * Number of profile searches [mins]	-0.0090	0.0037	-2.43	0.02**
CD * Driving distance before charging [mins]	-0.0036	0.0012	-2.92	0.00**
CD * Number of daily activities [mins]	0.0054	0.0042	1.28	0.20
CISDE(t_0)[mins]	-0.0617	0.0177	-3.48	0.00**
CISDE(t_0) * Education – University [mins]	0.0214	0.0108	1.99	0.05**
CISDE(t_0) * Income – Very high [mins]	-0.0203	0.0135	-1.50	0.13
CISDE(t_0) * Electric vehicle access [mins]	-0.0019	0.0016	-1.21	0.23
CISDE(t_0) * EV Loyal Enthusiasts [mins]	0.0188	0.0125	1.50	0.13
CISDE(t_0) * Driving EV more than one year [mins]	-0.0282	0.0105	-2.69	0.01**
CISDE(t_0) * Driving distance after charging [mins]	0.0063	0.0019	3.32	0.00**
CISDE(t_0) * Work based tour [mins]	-0.0257	0.0135	-1.90	0.06*
Scale for recruitment channel (η)	0.314	0.0617	5.09	0.00**
Number of estimated parameters	32			
Number of individuals	118			
Number of observations	1062			
Null log-likelihood	-736.122			
Final log-likelihood	-585.566			
Likelihood ratio index ρ	0.203			
Adjusted likelihood ratio index $\bar{\rho}$	0.160			

Regarding the **price** coefficient, younger people (up to 39 years old) are less cost-sensitive than older people. In addition, individuals that are employed seem to have a higher sensitivity to price than students, retired or unemployed individuals. These outcomes are in opposition with the findings in Daina (2014). Nevertheless, a cross-tabulation of age bands with income showed that the proportion of younger people with a net annual income that exceeds £40,000 (36.8%) is higher than the respective proportion of older people (34.5%). In the same direction, the dummy variable for employed individuals has a significant positive correlation with some of the other variables that are interacted with charging price (e.g. age less than 39, having children and work-based tour) therefore the negative sign could partly be explained by the positive sign of these parameters.

Drivers who are classified as EV "loyal enthusiasts" tend to be less cost-sensitive than other drivers while individuals that have stated that their longest driving distance between two consecutive charging events is less than 20 miles are more likely to be affected by price than other EV drivers or non-EV drivers. Finally, when there is a working activity included in the daily schedule, the negative effect of the combined parking-and-charging price is lower than in other cases.

People who are married tend to be less concerned about **walking time**, compared to other people. Similar is the indication for individuals that live on their own. The combined effect of the two parameters shows that households with more than three residents (e.g. families with children) have the higher sensitivity to walking time. Moreover, EV drivers that have been already using out-of-home charging places to plug-in their vehicles are less sensitive to walking time than other drivers.

The effect of **charging duration** on choice outcomes is less intuitive than the other parameters. After accounting for systematic heterogeneity, it can be observed that the sensitivity towards charging duration varies in sign across the survey respondents. As it was explained for the base specification, there is a net positive marginal utility for longer charging events.

In order to test if this effect is partially attributed to the selection of recruitment channels, the sample was split in Panelbase respondents and internally recruited respondents and the estimation results are presented in Table B.1 of Appendix B. It is observed that the coefficient for charging duration is positive for both samples but statistically significant only for the Panelbase sample, similar to the base specification in Table 4.3[41].

The positive effect of charging duration is stronger for employed individuals, which could be possibly explained by the longer dwelling times at their workplace, compared to individuals that charge their cars at other out-of-home locations (e.g. shopping or leisure). As a matter of fact, there is a positive significant correlation between work-based tours and parking durations. On the other hand, the positive effect of charging duration is weaker for individuals who have reported their ethnicity as white and for individuals that have to drive a longer distance before they reach the charging location.

One marginal effect that is hard to interpret is the higher sensitivity to charging duration for those that performed a higher number of searches in order to find a suitable travel profile. Since the number of searches is positively correlated with the number of daily activities, it can be assumed that these respondents were looking for more complex trip-chains that would represent better their daily schedule. Combining the two interaction terms, the net negative effect becomes smaller.

Regarding the **CISDE** coefficient, individuals with a university degree have a lower sensitivity to changes in departure time from home. A possible explanation may be that those with a higher education level understand the caveats from charging their vehicle in a high-peak period and hence they are willing to shift slightly their schedule in order to improve social welfare.

In addition, experienced EV drivers tend to be more sensitive to changes in departure time than new EV drivers or non-EV drivers. Increasing driving distances after the charging event are related with a lower negative effect for schedule delays. Finally, individuals that undertake work-based tours are more likely to be sensitive to travel timing modifications. This result is intuitive, and it can be attributed to the reduced flexibility of working activities.

To summarise, the estimates for the interaction terms of socio-demographic, travel and charging preferences with the charging attributes of the SP experiment should be considered as the result of an empirical analysis with the existing dataset and it would be difficult to generalise the conclusions without the collection of further data from different spatial settings.

[41] It is interesting to note here that the adjusted $\bar{\rho}$ for the smaller sample of internally recruited respondents is significantly higher than this of Table 4.5 (0.308 vs 0.160).

The willingness to pay (WTP) for the various charging attributes can be estimated as the ratio between their marginal utilities and the price coefficient[42]. For example, the minimum WTP for a reduction in walking time is equal to 1.8p/minute, while the maximum is 3p/min. Likewise, the minimum monetary value of schedule delay is 0.6p/minute, and the maximum is 11p/minute. This means that the average monetary value of CISDE is equal to £3.48/hour, which is in line with the estimates of Hess et al. (2007) for schedule delays in a time-of-day choice model.

Finally, the WTP for charging duration is in the range of -1.1p/minute – 1.1p/minute. In other words, there are some people from the estimated sample that would pay for a reduction in charging duration while other would pay for an increase in charging duration. The preferences of the latter are difficult to explain behaviourally. Daina (2014) that has found similar results, attributed the preference for longer charging duration to a positive attitude towards smart charging, i.e. a willingness to benefit the society.

4.2.4.3 Mixed Logit model

Apart from the systematic heterogeneity that was presented in Table 4.5, the choice outcomes are also affected by random taste variations that could be captured with the use of a mixed logit specification. The random coefficients for the four charging attributes are modelled with a normal distribution in order to identify if there are large and significant variations after the correction for socio-demographics and other attributes. Even though the signs of these four coefficients are intuitive, the normal distribution is adopted because the heterogeneity around their mean values is already treated with the use of the interaction terms. It is also assumed that the random coefficients are independent and thus there is no covariance between them.

The parameter estimates of the mixed logit model are presented in Table 4.6. The inclusion of random taste variation increased the goodness-of-fit of the model ($\bar{\rho}$ = 0.170 instead of 0.160).

This relatively small differentiation might be due to overfitting and it would be useful to cross-validate the estimated values with another sample, in order to exclude this possibility.

[42] The WTP values are based only on the significant coefficients of Table 4.5.

Table 4.6: Mixed logit charging choice, "charging game" – final specification with interaction terms and random coefficients

Variables	Coefficient	Std error	t-test	p-value
ASCA	0.278	0.162	1.71	0.09*
ASCB	0	fixed	***	***
CP [£]	-3.370	1.320	-2.56	0.01**
CP * Age <39 [£]	0.841	0.410	2.05	0.04**
CP * Having Children [£]	0.199	0.385	0.52	0.61
CP * Employed [£]	-0.967	0.588	-1.65	0.10*
CP * EV Loyal Enthusiasts [£]	0.724	0.463	1.56	0.12
CP * Longest distance driven between charging events < 20 miles [£]	-1.23	0.738	-1.66	0.10*
CP * Work Based Tour [£]	0.787	0.528	1.49	0.14
CP * Initial State of Charge [£ * miles]	0.228	0.233	0.98	0.33
WT [mins]	-0.407	0.126	-3.23	0.00**
WT * Married or Domestic partnership [mins]	0.105	0.0637	1.65	0.10*
WT * Living alone [mins]	0.112	0.0774	1.45	0.15
WT * Free EV charging [mins]	0.186	0.132	1.41	0.16
WT * Charging out-of-home [mins]	0.0730	0.0505	1.45	0.15
WT * Weekday travel [mins]	0.0713	0.0540	1.32	0.19
WT * Number of daily activities [mins]	0.0171	0.0358	0.48	0.63
CD [mins]	0.00614	0.0218	2.82	0.00**
CD * Female [mins]	0.0051	0.0090	0.56	0.57
CD * Employed [mins]	0.0115	0.0058	1.99	0.05**
CD * Ethnicity – White [mins]	-0.0293	0.0135	-2.16	0.03**
CD * Number of profile searches [mins]	-0.0141	0.0062	-2.28	0.02**
CD * Driving distance before charging [mins]	-0.0044	0.0017	-2.54	0.01**
CD * Number of daily activities [mins]	0.0017	0.0036	0.48	0.63
CISDE(t_0)[mins]	-0.0781	0.0261	-2.99	0.00**
CISDE(t_0) * Education – University [mins]	0.0252	0.01062	1.55	0.12
CISDE(t_0) * Income – Very high [mins]	-0.0218	0.0223	-0.98	0.33
CISDE(t_0) * Electric vehicle access [mins]	-0.0027	0.0021	-1.26	0.21
CISDE(t_0) * EV Loyal Enthusiasts [mins]	0.0282	0.0199	1.42	0.16
CISDE(t_0) * Driving EV more than one year [mins]	-0.0515	0.0193	-2.67	0.01**
CISDE(t_0) * Driving distance after charging [mins]	0.0072	0.0030	2.36	0.02**
CISDE(t_0) * Work based tour [mins]	-0.0165	0.0198	-0.84	0.40
Scale for recruitment channel (η)	0.343	0.102	3.35	0.00**
Variance of charging price σ^2_{CP}	0.723	0.125	2.40	0.02**
Variance of walking time σ^2_{WT}	0.019	0.013	-3.85	0.00**
Variance of charging duration σ^2_{CD}	0.0003	0.000	-2.35	0.02**
Variance of charging induced schedule delay early $\sigma^2_{\mathrm{CISDE(t0)}}$	0.0016	0.000	3.32	0.00**
Number of estimated parameters	36			
Number of individuals	118			
Number of observations	1062			
Null log-likelihood	-736.122			
Final log-likelihood	-575.256			
Likelihood ratio index ρ	0.219			
Adjusted likelihood ratio index $\bar{\rho}$	0.170			

The signs and magnitudes of the coefficients are similar to the MNL estimates and hence they are not further commented. The interaction terms that become insignificant are: price and dummy for EV loyal enthusiasts, price and dummy for work-based tour, walking time and dummy for living alone, walking time and dummy for charging out-of-home, CISDE and dummy for university degree and finally CISDE and dummy for work-based tour. Apparently, the random terms of the mixed logit model capture the variability that was initially explained by the corresponding interaction terms.

The estimates for the variances of the charging coefficients are statistically significant but relatively small. Therefore, the heterogeneity is largely captured by the interaction terms, leaving a small random residual.

4.2.4.4 Hybrid Panel Latent Class (HPLC) model

By integrating latent psychological constructs, like attitudes and perceptions, into discrete choice models, it is possible to improve the understanding of an individual's choice process. Since the decision associated with the first SP experiment of the EV-PLACE survey is a synthetic process that combines the idiosyncratic preferences for parking, charging and activity planning, there is a wide set of attitudinal factors that could affect the choice outcome.

The required information was collected with the use of 16 attitudinal statements that covered several topics with potential relevance to the underlying charging choice. The respondents had to answer these statements on a five-point Likert scale where the first point was "strongly disagree", the fifth point was "strongly agree" and the in-between points expressed an intermediate level of agreement. The response to each statement served then as an indicator variable. The indicators I_1 - I_{16} and their descriptive statistics are analytically presented in Table 4.7. It must be noted that indicators I_{13} - I_{16} were originally based on a different question, nevertheless, they have been transformed to the same Likert-type scale, which reflects the willingness and/or need to search for parking.

A factorial analysis of the psychometric indicators allowed the identification of four latent constructs to be investigated: Schedule flexibility, perceived mobility necessity, inclination towards pre-planning travel activities and tendency to search for parking at the last moment. All these clusters of attitudes and perceptions entail an element of risk management and how drivers perceive uncertain travel conditions. The ambiguity in everyday choices of an EV driver (e.g. range anxiety, restricted charging infrastructure, time-of-use electricity tariffs etc.) is undoubtedly affected by latent psychological characteristics that are not observable.

Therefore, the statements presented earlier were originally included in the survey in order to explain latent effects that would be later integrated with the charging choices of the respondents.

Table 4.7: Attitudinal statements of the EV-PLACE survey and descriptive statistics of their indicators

Indicators	**Mean**	**Std dev**
I_1: I am more concerned about successfully reaching my destination in an EV than in a conventional vehicle	4.178	0.854
I_2: If there was a charging reservation system I wouldn't make a reservation unless I knew how much battery I needed for the rest of the day	3.686	0.949
I_3: If there was a charging reservation system I would always pay more to assure that I have extra energy in my vehicle in case I change my daily plan	3.254	1.056
I_4: I could have changed my departure time at the beginning of the day (earlier or later)	3.119	1.289
I_5: I could have performed the first activity of the day in another location	2.653	1.257
I_6: I could have performed the first activity of the day at another time	2.932	1.299
I_7: I could completely cancel the first activity of the day	2.381	1.287
I_8: A high level of mobility is required in order to organise my everyday life	3.907	0.961
I_9: I need to be mobile in order to take care of my everyday duties	3.958	0.831
I_{10}: My work requires a high level of mobility	3.331	1.220
I_{11}: When I make a reservation (e.g. air tickets, hotel, theatre) I always do it quite in advance so that I can find lower prices	3.856	0.880
I_{12}: I usually know my daily schedule when I leave home	4.068	0.803
I_{13}: Transformation of L_1*, willingness and/or need to search for parking at workplace	2.127	1.318
I_{14}: Transformation of L_2*, willingness and/or need to search for parking for shopping activities	3.195	1.303
I_{15}: Transformation of L_3*, willingness and/or need to search for parking for leisure activities	3.432	1.167
I_{16}: Transformation of L_4*, willingness and/or need to search for parking when visiting family/friends	2.729	1.454

**Parking search question: When you are looking for parking, which of the following sentences is more relevant to you according to the respective activity (L_1: Workplace, L_2: Shopping, L_3: Leisure, L_4: Visit family/friends)*

1. I always go to the same parking place

2. I have a private or reserved space

3. I go to the park nearest to my destination

4. I drive to my destination and then start to look

5. I drive around the streets looking for a free space

Table 4.8 shows the results of the factor analysis. The factor-loading threshold has been set to 0.4, so an indicator can belong to a factor only if it obtains a factor loading above 0.4. It is possible for each indicator to belong to more than one factors, yet, it can be observed that this is not the case here. For all groups, several indicators obtained high factor scores of the same sign. The fifth factor was excluded from the analysis because the signs are opposite and the meaning of the underlying attitude is not clear.

In this section, a latent class approach is used in order to perform the segmentation of EV drivers based on their charging behaviour. The attitudinal factors are used to explain the individual membership to various latent classes (Hurtubia et al. 2013). In this way, the researchers can link the attitudes of drivers with their probabilistic allocation to classes with heterogeneous preferences for out-of-home charging events.

On a first stage, the latent constructs are modelled as a deterministic linear function of the corresponding indicators. In other words, each factor is equal to the combined Likert-scores of the individual indicators and enters directly the class membership function. According to the results of this specification, the only constructs that had a statistically significant effect were those of the inclination towards pre-planning travel activities and the schedule flexibility.

Afterwards, the indicators were assumed to be measurable reflections of the related latent variables. The effect of these variables on charging preferences was estimated with the use of a hybrid choice model. This Hybrid Panel Latent Class (HPLC) model can correct for two problems of the deterministic approach: the measurement errors and the endogeneity between the choice and the level of agreement to the Likert-scale statements (Daly et al., 2012). Each latent variable, for this specification, adds a significant amount of parameters in the estimation process. As a result, it was decided to examine only the effect of pre-planning that was found to be significant before[43].

Pre-planning is an important dimension of scheduling decisions for urban travellers. Traffic congestion, activity-timing constraints and time-varying travel costs (e.g. congestion charges or dynamic parking tariffs) are some of the factors that restrict the impulsiveness for everyday trips. Nevertheless, impulsive behaviour is usually not deliberated, and hence, it is difficult to predict.

[43] The schedule flexibility latent variable was also tested with the hybrid specification but the level of statistical significance was similar to the pre-planning variable and the produced parameter estimates were less intuitive so it was rejected.

Table 4.8: Factor analysis of the attitudinal statements of EV-PLACE survey

Indicators	**Schedule flexibility**	**Perceived mobility necessity**	**Pre-planning**	**Parking search**	**Factor 5**
I_1: I am more concerned about successfully reaching my destination in an EV than in a conventional vehicle			0.464		
I_2: If there was a charging reservation system I wouldn't make a reservation unless I knew how much battery I needed for the rest of the day			0.551		
I_3: If there was a charging reservation system I would always pay more to assure that I have extra energy in my vehicle in case I change my daily plan					0.731
I_4: I could have changed my departure time at the beginning of the day (earlier or later)	0.698				
I_5: I could have performed the first activity of the day in another location	0.818				
I_6: I could have performed the first activity of the day at another time	0.847				
I_7: I could completely cancel the first activity of the day	0.817				
I_8: A high level of mobility is required in order to organise my everyday life		0.880			
I_9: I need to be mobile in order to take care of my everyday duties		0.854			
I_{10}: My work requires a high level of mobility		0.765			
I_{11}: When I make a reservation (e.g. air tickets, hotel, theatre) I always do it quite in advance so that I can find lower prices			0.751		
I_{12}: I usually know my daily schedule when I leave home			0.704		
I_{13}: Transformation of L_1*, willingness and/or need to search for parking at workplace					-0.619
I_{14}: Transformation of L_2*, willingness and/or need to search for parking for shopping activities				0.514	
I_{15}: Transformation of L_3*, willingness and/or need to search for parking for leisure activities				0.804	
I_{16}: Transformation of L_4*, willingness and/or need to search for parking when visiting family/friends				0.669	

As it is expected, the level of pre-planning differs by day of the week. For example, Doherty et al. (2002) found that last-moment decisions are more likely to take place on Saturdays. In addition, shopping or leisure trips are more likely to be impulsive than work-related trips, due to the re-occurrence patterns of the latter.

The limited driving range of electric vehicles and the sparse charging network might have a significant effect on the planning process for car-based daily tours. Some smart charging systems require the drivers' predictions for upcoming trip lengths and departure times in order to provide effective services (Hahnel et al., 2013). The type of the activity significantly affects these predictions, with work-related trips having the highest accuracy levels. Moreover, the continuous development of mobile applications could lead to charging reservation systems, similar to the example that has been designed for the EV-PLACE respondents (Ratej et al., 2013). As a result, it is important to understand how out-of-home charging choices are influenced by the propensity of an individual to reserve a charging post in advance.

Doherty and Miller (2000) discussed the planning process of individuals with the use of computerized scheduling decisions and discovered that most of the activities are planned either one day in advance or at the moment of departure. According to the same study, activity scheduling is influenced by the period elapsed between planning and time-of-departure. These findings could be compatible with the way people handle parking reservations as well.

The framework for HPLC model is presented in Figure 4.7. The structural equation of the latent variable model is the following:

$$X_n^* = \Lambda Z_n + \omega_n \quad and \ \ \omega_n \sim N(0, \Sigma_\omega) \tag{4.35}$$

where X_n^* is a scalar variable that represents the latent variable pre-planning, Z_n is a subset of the individuals' characteristics, Λ is the matrix of parameters to be estimated and ω_n is a random component that follows a normal distribution with zero mean and variance equal to Σ_ω.

The socio-demographics included as explanatory variables in the structural model are gender, age and income. Linking pre-planning with observable characteristics is not a straightforward process. It was hypothesized that this latent behaviour is associated with the lifestyle and the responsibilities of each individual, i.e. their life-stage, the number of people that are dependent on them and their everyday commitments (e.g. employment status). From the examined variables[44], the ones that were selected had the most significant effect, still, none of them is significant at the 0.1 level.

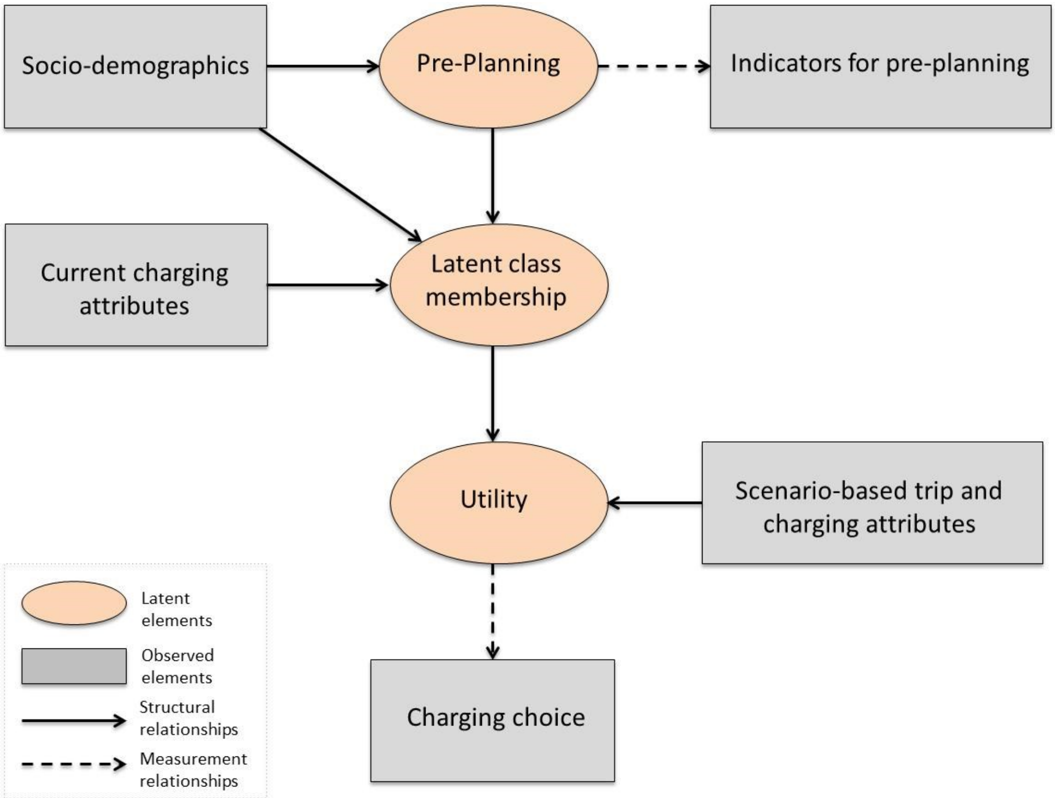

Figure 4.7: Framework for the empirical HPLC model with regards to charging behaviour for out-of-home activities

This is in agreement with Ben-Akiva et al. (2002b) who indicated that it might be a difficult task to find good causal variables for the latent variables. Another possible explanation is that the same socio-demographics are used as explanatory variables for the class-membership function. Therefore, it is difficult to find attributes that strongly affect the class-membership function, both directly and indirectly (through the pre-planning latent variable).

The random utility function is given by equation 4.33 and it is the same for the different segments. Therefore, the charging attributes and the scenario-based trip attributes enter the deterministic component of the utility in a linear way. The choice model has a panel latent class formulation where the probability is given by equation 4.20. The class-specific probability, assuming that the IID property holds for the error term, is as follows:

[44] Running an explanatory analysis, it was found that there are additional socio-demographic characteristics that interrelate with the pre-planning latent variable. However it was challenging to specify an identifiable ICLV model without removing some of the confounding variables.

$$P_n(i_{n,s}|X_i, Z_n, \beta_\kappa; \kappa) = \frac{e^{\beta_1^{\kappa\prime} X_{in,s}} + e^{\beta_2^{\kappa\prime} Z_n}}{\sum_{i=1}^{I} e^{\beta_1^{\kappa\prime} X_{in,s}} + e^{\beta_2^{\kappa\prime} Z_n}} \tag{4.36}$$

where $\beta_1^{\kappa\prime}$ is the class-specific vector of parameters for the alternative's characteristics and $\beta_2^{\kappa\prime}$ is the class-specific vector of parameters for the characteristics of the decision maker. The parameter vector for one of the classes is fixed to zero to secure the identification of the latent class model.

On the other hand, the class membership probability is given by:

$$P_n(\kappa|z_n) = \frac{e^{\delta_\kappa + \gamma_\kappa z_n + \theta_\kappa X_n^*}}{\sum_{l=1}^{K} e^{\delta_l + \gamma_l z_n + \theta_l X_n^*}} \tag{4.37}$$

where θ_κ is the coefficient for the latent pre-planning variable.

For the measurement equation of the latent variable model, it is acknowledged that Likert-type data have an ordered structure, and hence, the responses to the indicators of interest are modelled with ordered logit specifications (Daly et. al., 2012; Dimitropoulos, 2014; Hess et al., 2013). Therefore, the probability that an individual n provides response w to indicator t of the latent variable is:

$$\pi_{ntw} \equiv P_n(I_t = w) = \frac{e^{\tau_{tw} - \lambda_t X_n^*}}{1 + e^{\tau_{tw} - \lambda_t X_n^*}} - \frac{e^{\tau_{t(w-1)} - \lambda_t X_n^*}}{1 + e^{\tau_{t(w-1)} - \lambda_t X_n^*}} \tag{4.38}$$

where λ_t is the effect of X_n^* on indicator I_t and τ_{tw} (w=1,…,W) are cut-off values to be estimated. For identification, τ_{t0} is set to $-\infty$, τ_{tW} is set to $+\infty$, and λ_1 is set to 1. This approach is based on the normalisation strategy presented in Ben-Akiva et al. (2002b). Additionally, it is required to impose the constraint $\tau_{tw} \geq \tau_{t(w-1)}$. Also in order to fix the additive scale of w against the latent variable, the constant is omitted from the structural equation.

The measurement equation for the choice model is given by 4.18. The likelihood of jointly observing choice i and indicator w is given by the product of the respective likelihoods. As a result, the unconditional choice probability for the sequence of choices I_n can then take its final form, which is the following:

$$P_{I_n} = \int_{\omega_n} \sum_{\kappa=1}^{K} P_n(\kappa|z_n) \left(\prod_{s=1}^{S_n} P_n(i_{n,s}|X_j, Z_n, \beta_\kappa; \kappa)\right) \prod_{t=1}^{T} \pi_{ntw}\, \varphi(\omega_n) d\omega_n \tag{4.39}$$

where $\varphi(\omega_n)$ is the density of the error component of the structural equation.

The integrated model is estimated with Maximum Likelihood estimation. The choice and latent variable models were coded and simultaneously estimated in PythonBiogeme (Bierlaire, 2003, Bierlaire and Fetiarison, 2009).

The final specifications of the two latent class models (the PLC presented in Appendix B and the HPLC) are not the same with the mixed logit model estimated before, because some socio-demographics, trip and charging attributes have been removed in order for the former to be identifiable. In general, there are several domains of contrast between different types of models, thus making their comparison a challenging task (Greene and Hensher, 2003). For example, the evaluation of parameter estimates for the mixed logit and the latent class models cannot be informative because of the difference in scale between the two and their different levels of parameterization. A straightforward approach is to compare their statistical measures of fit. Nevertheless, additional metrics, like choice elasticities or willingness-to-pay estimates could be adopted for cross-comparison.

One basic advantage of the latent class model in contrast to the mixed logit is its semi-parametric specification that is not based on strong distributional assumptions about the unobserved heterogeneity. Moreover, the correlation between the parameters is implicit in the structure of the latent class model, while for the mixed logit the distributional form needs to be adapted in order to accommodate it (Hess et al., 2011). Based on empirical estimations the same authors have come to the conclusion that the latent class model should be considered at least as a viable alternative as the mixed logit model.

It is clear that both models have a superior statistical performance when compared with the MNL. On the other hand, the superiority of one over the other is inconclusive due to the fact that normal likelihood ratio tests cannot be applied. Shen (2009) applied a test for non-nested choice models and found that the latent class model has a better statistical performance compared to the mixed logit model. The same statistical test is applied to compare the mixed logit model with two latent class formulations: the PLC model (Table B.2) and a restricted version of the PLC model (Table B.3) that is based on the availability of socio-demographic and travel data and is going to be used for the segmentation of the revenue management application in Chapter 6. The model fit comparisons are also presented in Appendix B (Table B.4).

One significant issue that is raised with latent class models is the choice for the number of classes. This choice is made using the Bayesian information criterion (BIC):

$$BIC(model) = lnL(\hat{\beta}) + \frac{(model\ size)lnN}{N} \tag{4.40}$$

where $lnL(\hat{\beta})$ is the log-likelihood at the estimated parameters $\hat{\beta}$. The number of classes that minimises the BIC measure suggests which of the models is preferable. The segmentation of EV drivers has been tested with 2, 3 and 4 latent classes. The statistical fit was evaluated based on the BIC measure and the two-class model came out as the model with the best statistical performance (The BIC for the two classes was 2,693, for three classes 2,819 and for four classes 2,875).

The model components of HPLC are estimated simultaneously and the results for the random utility model are presented in Table 4.9 while the results for the latent variable model are presented in Table 4.10. Two indicators that verify the identification of the HPLC model are:

- The Hessian matrix of the log-likelihood function is non-singular
- The maximum likelihood estimation for model runs with different starting points converges to the same parameter values.

Based on the parameter estimates of the random utility model, the two classes of users are labelled as “price conscious” and “time conscious”. After simulating prior class membership probabilities with the use of 10,000 draws for the error component of the structural model, it is estimated that 77.9% of the users belong to the “price conscious” group while 22.1% of the users belong to the “time conscious” group.

Price-conscious users, as their label suggests, have a higher sensitivity to the combined charging and parking price than the time-conscious users. Within this class, the choice of those that perform a work-based tour is less affected by price than for those that perform a leisure or shopping-based tour. For them, travelling on a weekend is associated with a higher sensitivity towards walking time than travelling on a weekday. Moreover, the sensitivity to walking time is reduced when the number of activities that they have to undertake during the day increases. Finally, they have an implicit preference for longer charging durations for out-of-home events. The parameter of the alternative specific constant for this segment is positive, but not statistically significant.

Married people without children or people living alone are more likely to belong to the price-conscious class. Likewise, there is a propensity for older and for employed people (full-time, part-time or self-employed) to be members of this class.

Table 4.9: HPLC charging choice, "charging game" – latent class model with latent pre-planning variable

Variables	**Price-conscious users**		**Time-conscious users**	
Random Utility Model	Coefficient	Std. error	Coefficient	Std. error
ASCA	0.125	0.152	1.13**	0.508
ASCB	0	***	0	***
CP [£]	-1.56**	0.306	-0.957*	0.526
CP * Work-based tour [£]	0.522*	0.308	0.787	0.705
WT [mins]	-0.157**	0.0484	-0.0639	0.143
WT * Travel Profile – Weekday [mins]	0.0474	0.0333	-0.0936	0.131
WT * Number of activities [mins]	0.0502**	0.0253	-0.0909	0.0699
CD [mins]	0.0010**	0.0031	-0.0219	0.0141
CISDE(t_0)[mins]	-0.0240**	0.0056	-0.0745**	0.0295
Scale for recruitment channel (η)	0.371**	0.0698	0.371**	0.0698
Class Membership model				
Constant	1.22	2.42		
Female	0.326	1.51		
Age less than 40	-1.80	1.66		
Married	2.31*	1.40		
Employed	2.82*	1.55		
Very High Income	0.0516	1.22		
Ethnicity: White	-1.08	1.77	Reference class	
Having children	-2.56**	1.19		
Living alone	1.99	2.22		
Owning or leasing an electric vehicle	0.561	1.48		
Driving EV more than one year	-2.29*	1.28		
Charging out of home	1.25	1.63		
Pre-Planning	1.77	1.83		

Number of estimated parameters	53
Number of individuals	118
Number of observations	1062
Null log-likelihood	-2144.429
Final log-likelihood	-1161.694
Likelihood ratio index $\boldsymbol{\rho}$	0.458
Adjusted likelihood ratio index $\bar{\boldsymbol{\rho}}$	0.434

The ratio of non-EV drivers or individuals who have recently purchased an electric vehicle compared to experienced EV drivers is higher than for the "time-conscious" class. Their behaviour is in line with a higher probability that they already use out-of-home charging infrastructure to plug-in their vehicles. Finally, price-conscious users have an increased tendency to pre-plan their travel activities.

Time-conscious users have a higher sensitivity for the CISDE, i.e. they have a lower willingness to modify their travel time in order to find a preferable charging option. Moreover, they are more sensitive to walking time, but contrary to the members of the other class, they prefer to walk during the weekends and when they don't have a lot of activities to undertake throughout the day. They are negatively affected by longer charging durations, although this parameter is less statistically significant than for the price-conscious class. Finally, the class-specific parameter for the alternative specific constant is positive and significant, indicating an implicit preference for the unlabelled option that was presented at the top of the choice situation screen.

The time-conscious users are likely to be single or divorced and either unemployed or students or retired. Also, they are more experienced with driving an electric vehicle and less acquainted with recharging it out-of-home. Low inclination to travel pre-planning is another determinant of one's membership to this particular class.

The upper part of Table 4.10 shows the estimates of the structural model for the pre-planning latent variable. The findings show that women, older people and people with high income are less likely to pre-plan their travel activities.

The lower part of Table 4.10 shows the estimates of the measurement model. The signs of the lambdas are consistent with the *a priori* expectations, i.e. that individuals with a higher tendency to pre-plan their travel activities would express a higher level of agreement with the four statements presented earlier. Pre-planning behaviour is mainly expressed with the general preference towards early reservations and the likelihood of knowing the daily schedule before departing from home. Range concern and willingness to estimate battery requirements before making a charging place reservation have a smaller effect on the latent variable. As a result, charging service providers who are willing to collect attitudinal information from their EV customers in order to improve their revenue management system should focus on producing questions regarding past reservation for other services and on identifying the proportion of people that make impulsive travel choices. Nevertheless, the most statistically significant parameter is this of estimating battery needs before the reservation.

The minimum WTP for a reduction in walking time for the "price-conscious" users is equal to 4p/minute while the maximum is 15p/minute[45]. For the same class, the minimum monetary value of schedule delay is 1.5p/minute and the maximum is 2.3p/min. The respective values for the "time-conscious" class are higher, but they are not presented because the parameter estimates were not statistically significant. Finally the WTP for charging duration is in the range of (-0.09p/min) – (-0.06p/min) for the "price-conscious" users and in the range of (2.2p/min) – (12.9p/min) for the "time-conscious" users.

Table 4.10: Latent variable for HPLC charging choice, "charging game"

Variables					
Structural Model				Coefficient	Std error
ζ_{FEMALE}				-0.0785	0.142
$\zeta_{AGE\ LESS\ THAN\ 40}$				0.104	0.131
$\zeta_{VERY\ HIGH\ INCOME}$				-0.167	0.197
σ				0.483*	0.253
Measurement Model					
Range concern			**Reservation after planning**		
	Coefficient	Std. error		Coefficient	Std. error
λ_1	1	***	λ_2	2.15*	1.29
τ_{11}	-4.16**	0.726	τ_{21}	-5.24**	1.08
τ_{13}	-2.71**	0.625	τ_{23}	-2.29**	0.990
τ_{13}	-1.22**	0.330	τ_{23}	-0.65**	0.315
τ_{14}	0.96**	0.267	τ_{24}	1.72**	0.381
Early reservation			**Schedule knowledge**		
λ_{11}	2.59	1.76	λ_{12}	3.48	2.38
τ_{111}	-5.46**	1.12	τ_{121}	-5.98**	1.39
τ_{112}	-2.92**	0.988	τ_{122}	-4.03**	0.966
τ_{113}	-1.27**	0.364	τ_{123}	-2.41**	0.489
τ_{114}	1.65**	0.467	τ_{124}	1.40**	0.844

[45] The maximum values here represent those that performed a work-based tour.

4.3 Response to Dynamic Pricing

For a home-based electricity consumption context, dynamic prices can be too complex for the individual to process and make an informed decision. Therefore, it is usually assumed that a smart device is installed and controls the household’s appliances (Mohsenian-Rad and Leon-Garcia, 2010; Samadi et al., 2010). This *smart home* concept can significantly improve the results from dynamic pricing implementation.

What happens though when a smart device is not available and consumers need to make a decision based on imperfect information about real-time prices? Normally, they will form subjective probabilities for future electricity prices based on how they perceive the current price pattern. If they don’t change their consumption patterns, it is highly likely that dynamic pricing will incur additional costs rather than benefits to them.

One representative econometric analysis in order to identify the response of residential customers to the dynamic pricing of electricity is presented in Rasanen et al. (1995). In this study, it is assumed that individuals know the distribution of daily rates and on this basis, they pre-plan their energy consumption at the beginning of the day. However, the existence of stochastic needs during the day (e.g. additional heating) adds an element of uncertainty to the demand.

In Khan (2012) demand response is influenced by the estimated average price of electricity throughout the day. When the individual’s estimate of real-time electricity price is lower than the average estimate, then his utility function is convex as the utility he gains from electricity consumption increases in an increasing rate. On the other hand, if his real-time price estimate is higher than the average estimate, the utility function becomes concave since his willingness to consume electricity decreases.

The vast majority of studies that investigate the response of customers to dynamic pricing can be found in the airline pricing literature. For air tickets, typical evolution of dynamic prices from the day the flight is posted until the actual day of departure is as follows (Anderson and Wilson, 2003):

1. Fares start at a relatively high level, targeted to the risk-averse individuals that tend to book their tickets very early.
2. There is a gradual price decrease, segmented towards the leisure travellers who have higher price sensitivity.

3. The fares steeply increase towards the end of the reservation period, targeted to the business travellers who have lower price sensitivity.
4. There is a possibility for last-minute discounted (standby) air tickets according to the remaining seat availability.

If a consumer is aware of this time-distribution and he is able to identify in which direction the current price is going to move, then it is possible that he will demonstrate *strategic purchase behaviour*. On the other hand, if consumers are not willing to strategize their time of purchase but prefer to make their buying choice immediately are referred to as *non-strategic* or *myopic*. Due to the transparency that Internet channels offer to airline tickets prices, half of the leisure users admit that they are searching for cheapest fare available.

There is an increasing interest to understand intertemporal price discrimination and strategic consumer behaviour towards these pricing regimes, especially during the last decade. The strategy followed by consumers is more straightforward for products or services that follow markdown policies (e.g. fashion retailers). Elmaghraby et al. (2001) indicated that instead of purchasing such a product, as soon as its price is below the perceived value of the individual, there is a likelihood that some will wait for the next price markdown.

On the other hand, for service providers that present similarities with the airline companies, the consumers' strategy is based on their belief that a cheaper fare class that is closed at the time being, will re-open in the future. Anderson and Wilson (2003) study consumer reaction in this scenario, but without explicitly modelling consumers' choices. This belief depends, amongst other factors, on the probability that the anticipated demand for more expensive fare classes will be realised. In econometric terms, this behaviour has been characterised as forward-looking, discounted expected utility (DEU) maximising behaviour. The main findings come in disagreement, with some studies indicating myopic behaviour while others confirm the existence of a behavioural process that is consistent with the DEU framework. In general, it can be concluded that strategic behaviour is context-dependent (Osadchiy and Bendoly, 2010).

Osadchiy and Bendoly (2010) have tested the heterogeneity of consumers regarding their risk perception when a markdown pricing mechanism is applied. Their modelling approach is based on a laboratory experiment where participants have the option to buy now or wait to acquire the same product at a lower price where the second option entails the risk of a sold-out. After controlling for the misperception of the availability risk, they have found that 74%

of their sample demonstrates a forward-looking behaviour. Also, they showed that risk perceptions had a higher dispersion and fewer people perceived correctly the risk when there was a lack of information.

Li et al. (2014), instead of assuming *a priori* that strategic consumers exist in the airline industry, estimate their proportion and if it is significantly different than zero they hypothesise forward-looking behaviour. Their findings show that this proportion varies between 5% and 20% according to the specific itineraries, the distance of the trips and the time before departure. In their paper they suggest that there are two alternative methodological approaches that can be employed to estimate these proportions: 1) estimate the discount factor, a "continuous measure of consumers' patience", which is a computationally difficult approach [46] or 2) perform market segmentation between myopic and strategic users and estimate their fractions. Their empirical estimation with the second method is based on a very rich dataset with dynamic information for available prices and flight demands. On the other hand, Nair (2007) used the first approach to model the forward-looking behaviour of durable good consumers, with an application to the video-game market in U.S.

Lee et al. (2009) have developed a dynamic model in order to explain the online searching behaviour for air tickets, and the subsequent decision to buy the ticket or visit the online channel later. Consumers can be found in four possible states: Searching for a ticket, purchasing a ticket, leaving the system without purchasing but temporarily or leaving the system forever without purchasing. Their model is a Markov chain that is parameterised with the discount rate.

Su (2007) distinguishes the two dimensions of heterogeneity that exist under dynamic pricing schemes: the first is the heterogeneity across product valuations and the second is the heterogeneity in the degree of patience or in their cost for waiting a better offer. Their methodology allows the arbitrary combination between strategic and myopic behaviour instead of pure segmentation amongst them.

Baucells et al. (2014) deviate from the widely adopted discounted expected utility framework and model the "buy-or-wait" decisions in markdown management environments with a generalised approach that captures behavioural anomalies. One typical anomaly that has been studied in the relevant literature is hyperbolic discounting, i.e. a decreasing sensitivity to

[46] This difficulty entails identification issues related with the discount factor; hence analysts usually fix the value of the discount factor and perform sensitivity analyses around this value.

delays when the consequences are far into the future. Another irregularity is the hypothesised *sub-endurance* effect, assumed to be driven by the magnitude of the discount. In other words, customers demonstrate a higher patience in anticipation of larger discounts. This generalised model is reduced to a prospect theoretical approach for immediate purchases and to a hyperbolical discount specification for future purchases with certain product availability.

The authors of the above paper suggest that the trade-offs of such a choice problem are four: the value of the product, the magnitude of the future discount, the probability of finding the product later and the disutility by the purchase delay. Also, there are three interrelated dimensions that need to be considered: risk, time and payoff. Based on empirical data, individuals have consistent indifference points where they switch from buying to waiting decisions. This is one of the few studies that have employed Prospect Theory methods to explore the response to dynamic pricing and from this aspect it has similarities with the risky choice framework developed later.

In this dissertation, response to dynamic pricing is measured trough the "buy or wait" choice of the booking game, described in Chapter 3. The probabilities of the expected outcomes are not subjective but are deterministically provided by an intermediate agent who is better informed than the individual EV driver. As a result, this is a typical problem of decision making under risk. It is noted at this point that decision-making under risk is not the same as decision-making under uncertainty (Batley, 2007). For risky choices, the individual is aware of the probability distribution of each prospect. On the other hand, this distribution is neither known nor it can be defined for choices under uncertainty.

4.3.1 Expected Utility Theory (EUT)

The first and most widely adopted framework for risky choice modelling is the Expected Utility Theory (EUT). This theory was first suggested by Bernoulli in 1738, who assumed that people instead of comparing gambling outcomes based on their monetary values, use their desirability for money, i.e. their subjective utility. According to EUT, which was further developed by Von Neumann and Morgenstern (1947), the utility function of an individual is expressed as follows:

$$u(s^n) = \sum_{k=1}^{K} p_k^n v(s_k^n) \qquad (4.41)$$

where s^n={s_k^n; 1≤k≤K} is an alternative (or concept) characterised by a set of K possible outcomes, p_k^n is the probability associated with the kth outcome and $v(s_k^n)$ is the "value" of the

k^{th} outcome for prospect s^n. In a lottery game for example, if one alternative has two possible outcomes: win k_1=£50 with p_1^n = 80% or lose k_2=£10 with p_2^n = 20%, then the expected utility of this alternative is (0.8)*50 – (0.2)*10 = £38. If there is another alternative with the same payoff (£38) but without uncertainty, it is possible to estimate an individual's attitude towards risk. For example, if an individual prefers the alternative with the certain payoff he can be characterised as *risk avert*, if he prefers the alternative with the risky alternative he can be characterised as *risk-prone* and if he is indifferent between the two he can be characterised as *risk neutral*. Mathematically, if there are two possible outcomes, s_1 and s_2, attitude towards risk can be expressed as:

- Risk avert: $u(p_1s_1 + p_2s_2) > p_1u(s_1) + p_2u(s_2)$
- Risk prone: $u(p_1s_1 + p_2s_2) < p_1u(s_1) + p_2u(s_2)$
- Risk neutral: $u(p_1s_1 + p_2s_2) = p_1u(s_1) + p_2u(s_2)$

The intuitive appeal and the convenience of the mathematical formulations above are the reasons that EUT was the prevailing approach in this research field for many decades. Nevertheless, latest studies in experimental economics have challenged the validity of this theory.

The first convincing arguments that expected utilities are not representative of observable choices have been demonstrated with the *Allais paradox* (Allais, 1953). This paradox illustrated that one of the axioms of EUT, the independence axiom[47], is not always valid. Further studies identified different violations of EUT, leading to the conclusion that decision-making under risk is influenced by misconceptions, biases and errors from the individuals. Therefore, non-EUT alternatives started to emerge in order to capture better the human behaviour.

4.3.2 Non-Expected Utility Theory (Non-EUT)

It is very common that individuals misperceive the real probability distribution and thus, subjective probabilities should be taken into account instead of objective probabilities. Objective probability can be described as the reflection of empirical frequencies of repeated events and it is uniform for decision-makers. On the other hand, subjective probabilities differ

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[47] According to the *independence axiom* if two gambles A and B have a certain preference order (i.e. A≥ B), when they are mixed with a third gamble C, they maintain the same preference order (i.e. for p∈(0,1] $pA + (1-p)C \geq pB + (1-p)C$

from person to person based on their tastes and perceptions and they might even change for a specific person under various choice contexts.

The most prominent non-EUT methods, which are presented here and have been employed for the empirical estimation, are Rank-Dependent Expected Utility Theory (RDEU) and Prospect Theory (PT). The general idea for these methods is that weighting functions are used to transform the objective probabilities into subjective ones.

Even though the non-EUT field has demonstrated a great progress lately, it still cannot be declared with certainty that it outperforms traditional EUT approaches. This is largely attributed to the fact that there is not enough empirical evidence to prove the superiority of non-EUT over EUT, regarding model performance. Non-EUT, in principle, has been established on experimental observations and it cannot be guaranteed that the violations of EUT found in laboratory are transferable in the real world.

4.3.2.1 Rank-Dependent Expected Utility (RDEU) Theory

In RDEU that was first developed by Quiggin (1982), the weighting function depends on the ranking of prospective outcomes. Hence, if there is a prospect $s^n = (s_1^n, s_2^n, \dots, s_k^n; p_1^n, p_2^n, \dots, p_k^n)$ where $s_1^n \leq s_2^n \leq s_k^n$ are the possible outcomes, ranked from the worst to the best, then expected utility can be written as:

$$u(s^n) = \sum_{k=1}^{K} w(s_k^n) u(s_k^n) \tag{4.42}$$

where the decision weights are:

$$w(s_k^n) = \begin{cases} \pi(p_k^n, p_{k+1}^n, \dots, p_K^n) - \pi(p_{k+1}^n, p_{k+2}^n, \dots, p_K^n) & if\ 1 \leq k < K \\ \pi(p_K^n) & if\ k = K \end{cases} \tag{4.43}$$

and $\pi(.)$ is the increasing weighting function with $\pi(0) = 0$ and $\pi(1) = 1$. Also, $\pi(p_k^n, p_{k+1}^n, \dots, p_K^n)$ is the weight associated with obtaining outcome k or better than k. In other words, the decision weight expresses the difference between the distortions of cumulative probabilities. Ranking effect on the weighting function means that individuals are considered to pre-process how good or not each outcome k is.

If $\pi(.)$ is convex then decision-makers are assumed to be optimistic or risk-prone. On the contrary, if it is concave they are assumed to be pessimistic or risk avert. It is likely that the weighting function is not strictly convex or concave but it has a mixed specification. The most commonly encountered are the inverse S-shaped weighting functions (Figure 4.8). Two typical weighting functions that result into an inverse S-shaped curve are:

Quiggin $$\pi(p_k^n) = \frac{(p_k^n)^\gamma}{((p_k^n)^\gamma + (1-(p_k^n))^{\frac{1}{\gamma}}} \quad , with\, \gamma > 0.290 \tag{4.44}$$

Prelec $$\pi(p_k^n) = \exp(-a(-lnp)^\gamma) \quad with\, a > 0;\, \gamma > 0 \tag{4.45}$$

where γ is a parameter that defines the form of the inverse S-shape and a represents the individual's pessimism.

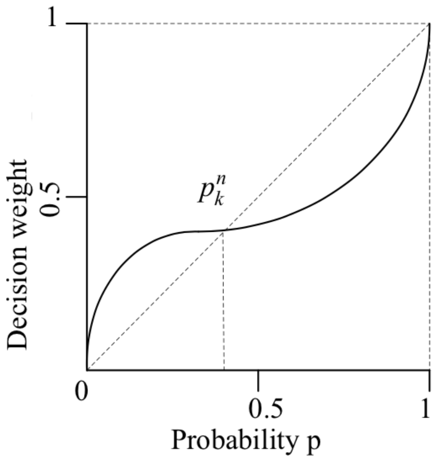

Figure 4.8: Inverse S-shaped weighting function for RDEU with crossover at $p_k^n = 0.5$. Reproduced from (Hu, 2013)

In this specification, small probabilities are over-weighted while large probabilities are under-weighted. Moreover, there is a crossover point where $\pi(p_k^n) = p_k^n$ which defines the shape of the function. Quiggin (1982) has assumed that this crossover point is $p_k^n = 0.5$.

4.3.2.2 Prospect Theory (PT)

The essence of Prospect Theory, which was introduced by Kahneman and Tversky (1979), is that outcomes of a gambling choice are interpreted as gains or losses compared to a specific reference point. The reference point of the PT approach is quite appealing because decision-makers are likely to maintain their status quo (*endowment effect*) or compare the possible outcomes with the status quo (*anchoring effect*).

The prospect $s^n = (s_1^n, s_2^n, \dots, s_k^n)$ is now split into losses $s^{n-} = (s_1^{n-}, s_2^{n-}, \dots, s_i^{n-})$ and gains $s^{n+} = (s_i^{n+}, s_{i+1}^{n+}, \dots, s_K^{n+})$ based on the outcome's relative point to the reference outcome s_{ref}^n. The two-part utility function can be expressed as:

$$u(s_k^n) = \begin{cases} (v(s_k^{n+}) - v(s_{ref}^n))^a \\ -\lambda(v(s_{ref}^n) - v(s_k^{n-}))^\beta \end{cases} \quad (4.46)$$

where λ is an indication of loss aversion and it is greater than one if the individual is loss avert. Also, $a, \beta < 1$ are parameters that express the degree of diminishing sensitivity. In Figure 4.9 it can be observed that the utility function has a kink point at s_{ref}^n and the slope is steeper for losses than for gains ($h_l > h_g$), suggesting loss aversion. Moreover, the function is concave in gains and convex in losses, demonstrating a decrease in marginal utility as the difference from the reference point increases. One of the most significant findings in PT is the asymmetry in preferences between gains and losses i.e. the existence of loss aversion.

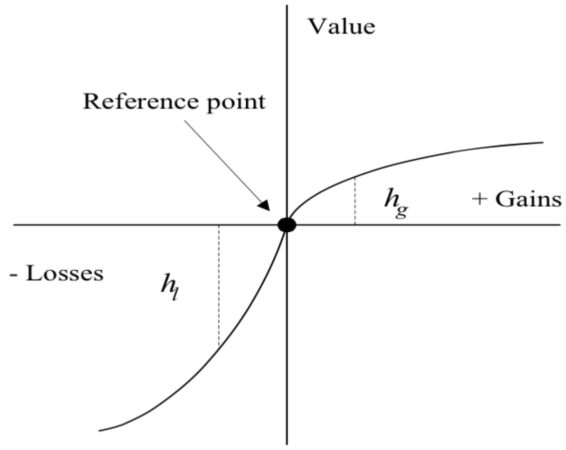

Figure 4.9: Value function based on PT approach. Reproduced from (Hu, 2013)

4.3.3 Practical applications of EUT and non-EUT

EUT and non-EUT methods have been widely adopted in transportation research, especially during the last decade. Examples of their applications can be found in equilibrium modelling, valuation of travel time or attitudes towards travel time uncertainty and experience/learning in travel choices (Kemel and Paraschiv, 2013). The majority of these applications are based on stated preference surveys because of the level of control that they offer to the analyst. In experimental economics it is common to adopt an intermediate approach between stated and revealed preferences, i.e. incentivised laboratory experiments. Nevertheless, transport choices are more complex since they do not involve only money, but other characteristics as well (e.g. time or comfort).

For risky choices in transport applications, EUT was often embedded with random utility models (RUM) creating an *ad hoc* modelling approach. Integrating these two theories provides the possibility to represent simultaneously two distinct sources of uncertainty: the uncertainty of the decision-maker when presented with various possible outcomes (EUT) and the uncertainty of the researcher when observing the choice process of the decision-makers (RUM). The integrated RUM-EUT model is formed by adding an RUM-related error term to the value term of the EUT model of equation 4.41:

$$u(s^n) = \sum_{k=1}^{K} p_k^n [v(s_k^n) + \varepsilon^n] \tag{4.47}$$

Such integration is governed by some important conceptual shortcomings that have been addressed by the framework of Liu and Polak (2007). This framework allows the explicit modelling of attitudes towards risk independent of the conventional RUM-like tastes.

It is assumed that $\beta_i = \{\beta_{ir;}1 \leq r \leq R\}$ is a set of taste parameters associated with the vector of observable attributes $A = \{a_m 1 \leq m \leq M\}$ that affect the choice behaviour. Taste parameters are individual-specific and they are characteristic of a riskless choice. Each individual i attaches a scalar value ${v_{ik}}^n$ to the kth outcome of prospect s^n which is a function of β_i, i.e. ${v_{ik}}^n = f(s_k^n, \beta_i)$. The scalar value for prospect s^n (${u_i}^n$) is a function of ${v_{ik}}^n$, the probabilities associated with prospect outcomes p^n and a set of extra parameters $\varphi_i = \{\varphi_{ir}; 1 \leq r \leq T\}$ that are representative of decision-making under risk. Hence, it can be denoted as $u_i^n = g(v_{i1}^n, \ldots, v_{iK}^n p_1^n, \ldots, p_K^n, \varphi_i)$.

Allowing some relaxation in EUT, each outcome s_k^n instead of being evaluated based on its riskless value ${v_{ik}}^n$ can be evaluated based on a non-linear function z(${v_{ik}}^n, \varphi_i$). When this function is concave, then the expected utility is lower than the expected value and hence the individual is risk-averse. On the other hand, when this function is convex the individual is risk prone. A typical non-linear transformation of the value function is when the individuals are characterised by constant absolute risk aversion (CARA), i.e. the risk attitudes for a particular prospect are not affected by the value of the outcomes involved in this prospect. The functional form of CARA is $z(x) = (1 - e^{-ax})/a$ where a positive a expresses risk proneness while a negative a expresses risk aversion.

Integrating EUT and RUM, the scalar value for prospect s^n can now be transformed to:

$$u_i^n = \sum_{k=1}^{K} z({v_{ik}}^n, \varphi_i) p_k^n + \epsilon_i^n \tag{4.48}$$

where ϵ_i^n is the unobservable component[48] of the utility associated with prospect s^n and ${v_{ik}}^n = w_{ik}^n + \eta_{ik}^n$ is the combination of observable and unobservable components of the value function associated with outcome k.

In their majority, individuals are risk-averse and in a dynamic pricing context, they tend to choose a certain price over an uncertain one (Bonsall and Shires, 2005). Moreover, it has been found that the upper end of the price distribution disproportionally affects their choice. For example, EV drivers would avoid charging their vehicle during a specific period if there was a possibility of a very high cost.

The assessment of state-dependent prices, according to empirical evidence, strongly depends on individuals' expectations (Lindsey, 2011). The judgement of dynamic prices is affected by historical prices as well as by prices charged for similar services or under similar circumstances. These reference-dependent effects are likely to decay for increasing experience with the price mechanism, as individuals become more familiar with gains and losses. Potentially, this is the reason dynamic pricing has become acceptable for airline tickets and other travel-related services (e.g. dynamic tolls).

Prospect theory is suitable for modelling the response to price signals because it has been observed that choices depend on how the individual perceives the monetary transaction: in a positive or negative way. For example, paying for out-of-home charging might be considered as a loss, due to the fact that this service is free for most of the respondents at the time being.

4.3.4 Empirical estimation

For the booking game of the EV-PLACE survey, as it was presented in Chapter 3, respondents had to choose between one certain and one risky alternative according to the activities and the timings of the home-based tour that they have selected earlier. The background characteristics like the location of the charging post were similar to the charging game. Also, the charging attributes, i.e. charging duration, CISDE and walking time to the destination, were randomly selected from the design levels of the previous SP exercise and were fixed across the choice situations.

Respondents are presented with a deterministic price ("BOOK NOW", the safe option) and with a random price ("BOOK LATER", the risky choice). Specifically, C_N is the deterministic price of the "booking now" choice, C_D is the decreased potential price of the risky choice while

[48] Note that the error term ϵ_i^n applies now to the whole prospect and not to the expected term as in equation 4.47. This modification makes the model more tractable, taking into account the nonlinearity of the value function.

C_I is the increased potential price of the risky choice. If the integrated RUM-EUT is treated as the basic model specification, then the utility functions for the two booking alternatives, for the riskless form of 4.48, are given by:

$$u_i^{NOW} = ASC^{NOW} + \beta_C C_N + \varepsilon_i \tag{4.49}$$

$$u_i^{LATER} = ASC^{LATER} + \beta_C[P_I C_I + (1 - P_I)C_D] + \varepsilon_i \tag{4.50}$$

where P_I is the probability for a future increase in price, $(1 - P_I)$ is the probability for a future decrease in price, ε_i is the error associated with the analyst's observations, ASC^{NOW} and ASC^{LATER} are the alternative specific constants and β_C is the sensitivity to price.

The estimation of the model was carried out with BIOGEME 2.2 (Bierlaire, 2003). Like for the charging choice model in subsection 4.2.4, a scale parameter is estimated in order to reduce the variance of the error term for the Panelbase respondents. The parameter estimates and the goodness-of-fit of the model are presented in Table 4.11.

The results of the RUM – EUT model are quite intuitive, with a positive constant for the "book now" option (i.e. an implicit preference for the non-risky choice, indicating a tendency towards myopic behaviour), and a statistically significant negative coefficient for the charging price, which is very close to the estimation from the charging game ($\beta_{CP} = -0.918$ in Table 4.4).

Table 4.11: RUM – EUT model, booking game – base specification

Variables		**Coefficient**	**Std error**	**t-test**	**p-value**
ASC_{NOW}		1.18	0.139	8.45	0.00**
ASC_{LATER}		0	fixed	***	***
CP [£]		-0.899	0.121	-7.32	0.00**
Scale for recruitment channel (η)		0.600	0.0907	-4.41	0.00**
Number of estimated parameters	3				
Number of individuals	118				
Number of observations	1062				
Null log-likelihood	-736.122				
Final log-likelihood	-602.236				
Likelihood ratio index $\boldsymbol{\rho}$	0.182				
Adjusted likelihood ratio index $\bar{\boldsymbol{\rho}}$	0.178				

In order to capture systematic heterogeneity and the effect of socio-demographics and other attributes on the booking choice, equation 4.49 is transformed to:

$$u_i^{NOW} = ASC^{NOW} + \beta_C C_N + \beta_X' \boldsymbol{X} + \varepsilon \qquad (4.51)$$

where $\boldsymbol{X}$ is the vector of personal attributes and β_X' is the associated vector of parameters to be estimated. Several specifications have been tested and the majority of the variables that enter the utility function are similar with the MNL model for the charging game. Additional (or modified) explanatory variables are presented below:

- Age group (**Over 60**, Less than 60)
- Travel profile frequency (**Undertake the selected travel profile every day,** undertake the selected travel profile less frequently)
- Schedule Flexibility (Combined Likert scale values of the indicators presented in subsection 4.2.4)
- Charging frequency (**Charging the EV more than once a day,** Charging the EV less than once a day, Non-EV drivers)
- Daily mileage with EV (**Driving more than 40 miles a day with EV,** Driving less than 40 miles a day with EV, Non-EV drivers)

The estimates for the full specification, after accounting for systematic heterogeneity, are shown in Table 4.12.

Following the framework of Liu and Polak (2007), the CARA functional form has been adopted for the non-linear transformation of the value function[49]. The non-linear formulation allows the researchers to investigate the decision maker's attitude towards risk in the dynamic pricing environment. The utility function for the risky alternative is now:

$$u_i^{LATER} = ASC^{LATER} + \beta_C \left[P_I\left(1 - e^{-aC_I}\right)/a + (1 - P_I)\left(1 - e^{-aC_D}\right)/a)\right] + \varepsilon_i \qquad (4.52)$$

The estimation results from the non-linear transformation are presented along with the riskless value function in Table 4.12.

The goodness-of-fit for the full specification of the linear model is significantly improved compared to the base specification ($\bar{\rho}$=0.232 vs $\bar{\rho}$=0.178). According to the estimated parameters, older individuals are more likely to choose the safe option compared to younger individuals. Similar are the findings for employed individuals. Under a different risky context, Daina (2014) has also found that older groups and people with full-time employment

[49] The constant relative risk-aversion (CRRA) transformation has been also tested with the empirical data but the results were quite similar to CARA so they are not presented here.

demonstrate a higher risk aversion, reflected by their increased sensitivity to a latent construct for range anxiety.

On the other hand, those that have children and a higher education level tend to exhibit a more strategic behaviour. Work-based tours are associated with a more conservative response to dynamic pricing, i.e. an increased preference for the "booking now" option. Finally, people that own or lease an EV are more risk-prone and are willing to wait for a better price.

Table 4.12: RUM – EUT model, booking game – full specification accounting for systematic heterogeneity

Variables	Linear function		Non-linear function	
	Coefficient	Std error	Coefficient	Std error
ASC_{NOW}	1.49^{*}	0.805	3.27^{*}	1.94
ASC_{LATER}	0	fixed	***	***
CP [£]	-1.12^{**}	0.162	-3.47^{**}	1.08
Age over 60	2.45^{**}	0.653	2.46^{**}	0.653
Employed	1.20^{**}	0.544	1.21^{**}	0.545
Having children	-0.546^{*}	0.322	-0.554^{*}	0.323
Education: University Graduate	-0.964^{**}	0.320	-0.977^{**}	0.323
Electric vehicle access	-0.847^{*}	0.509	-0.861^{*}	0.511
Number of daily activities	-0.272	0.229	-0.274	0.230
Number of profile searches	0.324^{*}	0.196	0.323^{*}	0.198
Travel profile – Every day	1.02	0.720	1.03	0.722
Travel day – Weekday	0.542	0.370	0.550	0.371
Work based tour	0.924^{**}	0.387	0.929^{**}	0.388
Schedule flexibility	-0.0376	0.0320	-0.0377	0.0321
Charge EV more than once a day	0.908^{*}	0.548	0.920^{*}	0.552
Charging EV cost – free	5.04^{**}	2.39	5.10^{**}	2.38
Driving EV more than a year	-1.01^{**}	0.323	-1.02^{**}	0.324
EV loyal enthusiast	0.792^{**}	0.322	0.800^{**}	0.324
Daily mileage with EV – more than 40 miles	-1.07^{**}	0.414	-1.09^{**}	0.417
Scale for recruitment channel (η)	0.416^{**}	0.0771	0.415^{**}	0.0762
Risk attitude parameter (α)	-	-	0.155	0.128
Number of estimated parameters	19		20	
Number of individuals	118		118	
Number of observations	1062		1062	
Null log-likelihood	-736.122		-736.122	
Final log-likelihood	-546.489		-545.749	
Likelihood ratio index $\boldsymbol{\rho}$	0.258		0.259	
Adjusted likelihood ratio index $\bar{\boldsymbol{\rho}}$	0.232		0.231	

EV drivers who stated that they charge their vehicle more than once a day demonstrated a myopic behaviour, which could be attributed to the planning burden associated with monitoring dynamic prices every time they charge. Furthermore, individuals that have been charging their EV for free, demonstrate a strong inclination towards the "booking now" option, possibly because they have a lower willingness to take the risk for an increased charging price. Experienced EV drivers have a lower likelihood of being myopic while those that are labelled as “EV loyal enthusiasts” have a lower likelihood of being strategic. Finally, individuals that have been regularly driving long distances with their electric vehicle prefer the risky choice. A potential explanation for their behaviour is that they are more familiar with risky situations, due to the fact that they repeatedly strain the limits of their battery range.

The goodness-of-fit for the non-linear transformation is slightly lower than the linear function and there is no significant difference in the parameter estimates. As with the case of mixed logit in 4.2.4.3, there could be an issue of overfitting, and cross-validation is required in order to identify it. The *alpha* parameter is not significant but this can be explained by the fact that risk aversion is captured by the coefficient for the alternative specific constant of the “booking now” option, which is positive and significant.

The non-EUT approaches presented in subsection 4.3.2 are also applied here, in order to identify misconceptions, biases and errors in the choice process of individuals.

First, the utility for the risky alternative is transformed based on the RDEU model as follows:

$$u_i^{LATER} = ASC^{LATER} + \beta_C\,[w(P_I)(1 - e^{-aC_I})/a + (1 - w(P_I))(1 - e^{-aC_D})/a)] + \varepsilon_i \qquad (4.53)$$

where w(.) is a function that reflects the individual weights towards risky outcomes and the outcomes are ranked in an increasing preference order (i.e. the increased price is ranked first and the decreased price is ranked second). This function is given by:

$$w(s_k^n) = \begin{cases} \pi(p_1^n, p_2^n) - \pi(p_2^n) & if\ k = 1 \\ \pi(p_2^n) & if\ k = 2 \end{cases} \qquad (4.54)$$

and $\pi(.)$ is the increasing weighting function of probability p_k^n with $\pi(0) = 0$ and $\pi(1) = 1$. Also, $\pi(p_1^n, p_2^n)$ is the weight associated with obtaining outcome 1 or better than 1.

The weighting function w(.) that is employed is this of equation 4.43, which results into an inverse-S shaped curve. The results from the estimation of the linear value function and the non-linear transformation under the RDEU model are presented in Table 4.13.

The model fit for the non-EUT models has not improved relative to the previous specifications. The signs and magnitudes of the estimates remain similar to the EUT model and like before, the parameter for the attitude towards risk is insignificant.

Table 4.13: RUM – RDEU model, booking game - full specification accounting for systematic heterogeneity

Variables	Linear function		Non-linear function	
Weighting function	$(p_k^n) = \frac{(p_k^n)^\gamma}{((p_k^n)^\gamma + (1-(p_k^n)^\gamma))^{\frac{1}{\gamma}}})$		$(p_k^n) = \frac{(p_k^n)^\gamma}{((p_k^n)^\gamma + (1-(p_k^n)^\gamma))^{\frac{1}{\gamma}}})$	
	Coefficient	Std error	Coefficient	Std error
ASC_{NOW}	3.07*	1.68	6.23*	3.49
ASC_{LATER}	0	fixed	***	***
CP [£]	-2.84**	0.552	-4.49**	1.60
Age over 60	2.53**	0.679	2.55**	0.680
Employed	1.26**	0.567	1.27**	0.567
Having children	-0.547*	0.329	-0.557*	0.332
Education: University Graduate	-0.982**	0.325	-0.999**	0.329
Electric vehicle access	-0.911*	0.534	-0.931*	0.537
Number of daily activities	-0.272	0.233	-0.274	0.235
Number of profile searches	0.330*	0.198	0.330*	0.200
Travel profile – Every day	1.02	0.739	1.04	0.743
Travel day – Weekday	0.537	0.382	0.547	0.383
Work-based tour	0.963**	0.401	0.972**	0.402
Schedule flexibility	-0.0380	0.0327	-0.0382	0.0329
Charge EV more than once a day	0.885	0.555	0.898	0.560
Charging EV cost – free	5.18**	2.51	5.25**	2.51
Driving EV more than a year	-1.02**	0.327	-1.03**	0.330
EV loyal enthusiast	0.802**	0.327	0.813**	0.330
Daily mileage with EV – more than 40 miles	-1.06**	0.420	-1.09**	0.424
Scale for recruitment channel (η)	0.396**	0.0758	0.395**	0.0742
Risk attitude parameter (α)	-	-	0.198	0.140
γ	1.30**	0.293	1.32 **	0.259
Number of estimated parameters	20		21	
Number of individuals	118		118	
Number of observations	1062		1062	
Null log-likelihood	-736.122		-736.122	
Final log-likelihood	-545.526		-544.518	
Likelihood ratio index $\boldsymbol{\rho}$	0.259		0.260	
Adjusted likelihood ratio index $\bar{\boldsymbol{\rho}}$	0.232		0.232	

The parameter γ is statistically significant for both specifications. As a result, it contains information about the individuals' perceptions of the probabilities for risky outcomes. The value of γ is close to 1 so the distortion of the objective probabilities is small. Nevertheless, instead of the commonly encountered inverse S-shape, this weighting function has the opposite effect. This means that individuals slightly underweight low probabilities and overweight high probabilities. The crossover point for the inverse-S curve is around 0.5. The relationship between probabilities and weighted probabilities for the linear value function (it is almost the same for the non-linear model) can be seen in Figure 4.10.

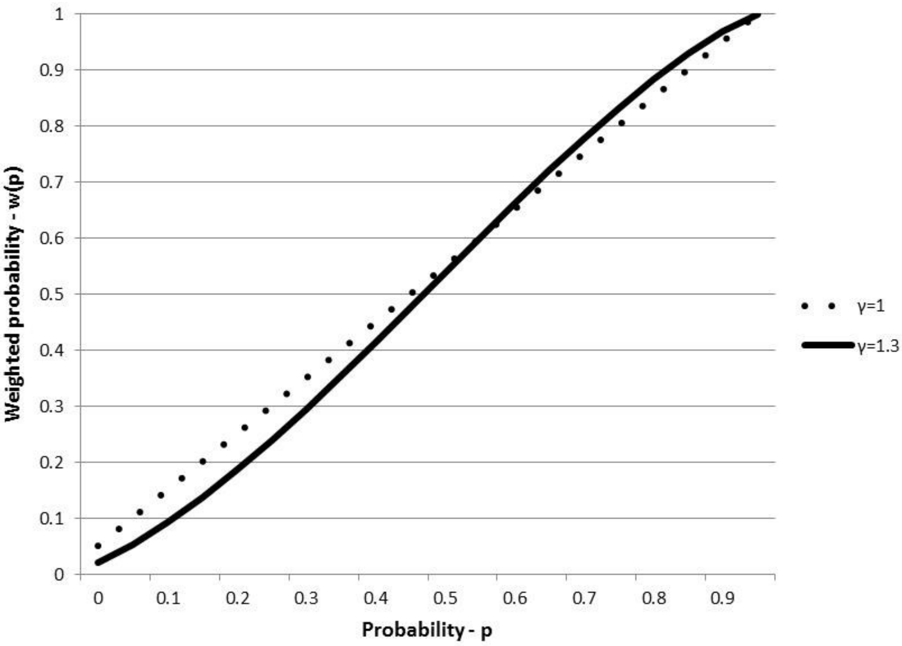

Figure 4.10: Objective and subjective probabilities of the risky outcomes

Since the probabilities of future prices are based on an orthogonal design, the aggregated probabilities for both outcomes throughout the choice experiment are 0.5 and, as a result, their decision weights are equal. The results suggest that when the probability of an increased price is small (i.e. 0.2 and w(0.2)<0.2 and 1-w(0.2)>0.8) then an increased price weights less than proportionally compared to the objective probability, reflecting optimism for the individuals. However, this optimism is small because γ is close to 1. On the other hand, when the probability of a decreased price is small, following the same logic, individuals show some pessimism and tend to be risk-averse.

Following the Prospect Theory approach, the utility function for the "booking later" can be expressed as follows:

$$u_i^{LATER} = ASC^{LATER} + \beta_{C(gain)}(1 - P_I)\left(C_{Ref} - C_D\right)^{a} + \beta_{C(loss)}P_I\left(C_I - C_{Ref}\right)^{\beta} + \varepsilon_i \qquad (4.55)$$

where C_{Ref} is the reference price, which due to the nature of the problem is assumed to be equal to the price for the safe choice, i.e. £2.50[50]. The cost coefficient is now divided into gain $\beta_{C(gain)}$ and loss $\beta_{C(loss)}$ based on the relative location of the outcome with respect to the reference price C_{Ref}. Finally, the parameters a and β reflect the degree of diminishing sensitivity.

[50] It has to be noted here that this price level might be non-representative of the existing recharging cost for EV drivers. In this case, it wouldn't coincide with the reference price from the revealed preferences of the individuals. Nevertheless, it is undoubtedly the "reference point" for the hypothetical choice of the booking game, based on which the comparison with the future prices is made.

Two PT models were estimated: one where the α and β parameters are fixed to one in order to capture only reference dependence, and one that allows the estimation of diminishing sensitivity. The estimation results are presented in Table 4.14.

Table 4.14: RUM – PT model, booking game - full specification accounting for systematic heterogeneity

Variables	**Reference dependence**		**Diminishing sensitivity**	
	Coefficient	Std error	Coefficient	Std error
ASC_{NOW}	2.14^{**}	0.927	2.76^{**}	1.03
ASC_{LATER}	0	fixed	***	***
CP Gain [£]	2.92^{**}	0.497	3.21^{**}	0.856
CP Loss [£]	-1.83^{**}	0.485	-1.33^{**}	0.514
Age over 60	2.47^{**}	0.654	2.55^{**}	0.677
Employed	1.21^{**}	0.544	1.26^{**}	0.565
Having children	-0.556^{*}	0.324	-0.558^{*}	0.331
Education: University Graduate	-0.981^{**}	0.324	-1.00^{**}	0.329
Electric vehicle access	-0.866^{*}	0.512	-0.922^{*}	0.533
Number of daily activities	-0.274	0.231	-0.276	0.235
Number of profile searches	0.323^{*}	0.198	0.330^{*}	0.200
Travel profile – Every day	1.04	0.724	1.04	0.743
Travel day – Weekday	0.553	0.372	0.552	0.383
Work-based tour	0.933^{**}	0.388	0.971^{**}	0.401
Schedule flexibility	-0.0379	0.0322	-0.0386	0.0329
Charge EV more than once a day	0.923^{*}	0.553	0.906	0.560
Charging EV cost – free	5.11^{**}	2.38	5.23^{**}	2.50
Driving EV more than a year	-1.02^{**}	0.325	-1.04^{**}	0.330
EV loyal enthusiast	0.804^{**}	0.325	0.818^{**}	0.330
Daily mileage with EV – more than 40 miles	-1.09^{**}	0.418	-1.09^{**}	0.424
Scale for recruitment channel (η)	0.414^{**}	0.0756	0.397^{**}	0.0738
$\boldsymbol{\alpha}$	-	-	0.960^{**}	0.249
$\boldsymbol{\beta}$	-	-	2.01^{**}	0.641
Number of estimated parameters	20		22	
Number of individuals	118		118	
Number of observations	1062		1062	
Null log-likelihood	-736.122		-736.122	
Final log-likelihood	-545.340		-543.597	
Likelihood ratio index $\boldsymbol{\rho}$	0.259		0.262	
Adjusted likelihood ratio index $\bar{\boldsymbol{\rho}}$	0.232		0.232	

The model fit is similar to the RDEU model and the results agree with the *a priori* expectations, i.e. the price coefficient is positive when the outcome is framed as a gain and negative when it is framed as a loss. While the positive and significant parameter for the constant of the "book now" option indicates a risk-aversion for both models, the absolute ratio of the cost coefficients

$|\beta_{C(loss)}/\beta_{C(gain)}|$ does not indicate a loss-aversion (0.63<1 for the first model and 0.41<1 for the second model).

On the other hand, the statistical significance of the parameters α and β shows an asymmetrical response to price increases and price decreases from the *status quo*, or, in other words, the certain price of the "booking now" option. This asymmetrical behaviour is differentiated between the loss and the gain space. The parameter α is smaller than 1, reflecting a diminishing sensitivity to decreasing prices while the parameter β is larger than one reflecting an increasing sensitivity to higher prices.

Note here that the taste parameters for charging cost depend on the probability of change and hence they reflect the sensitivity to a risky outcome with a weighted price. Since the attribute levels are based on an orthogonal design, the aggregate probability is 50% and all outcomes have equal weights. The changes in utility with respect to the changes in the weighted price of gain and the weighted price of loss are presented in Figure 4.11.

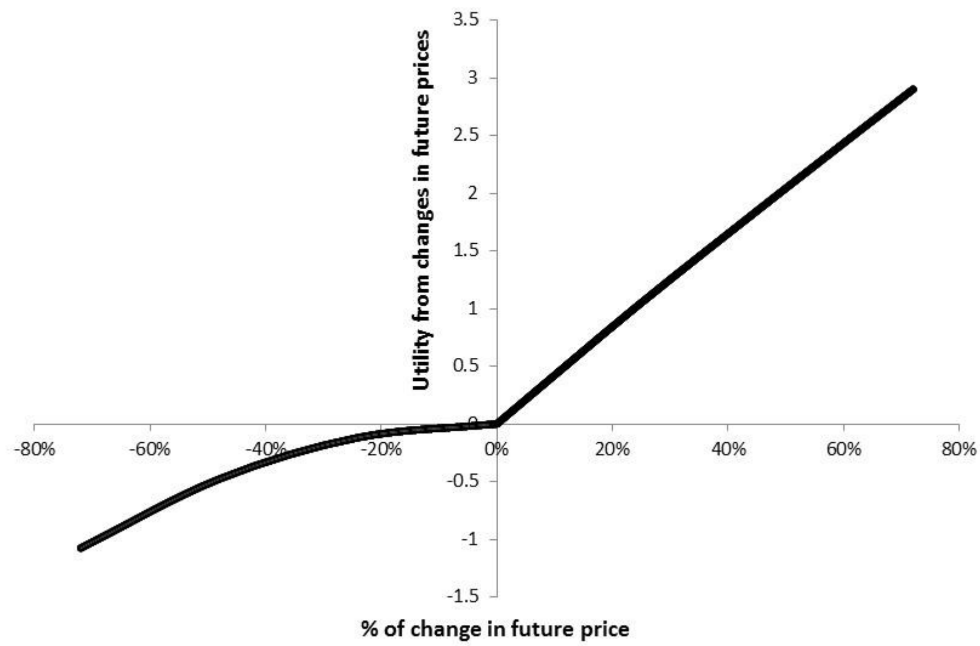

Figure 4.11: Asymmetrical preferences towards gains and losses from changes in future prices

The asymmetry can be observed both in absolute terms and in the shape of the curve. For example, the 80% decrease of price results into a utility increase of 3 units whereas a price increase of the same level results in a utility decrease of 1 unit. Furthermore, the relationship is almost linear in the gain space and concave in the loss space, indicating an increase in the absolute marginal utility as the difference from the reference price increases. The behavioural interpretation of the latter is that a £2.00 increase in charging price instead of being twice as bad as an increase of £1.00 is perceived as a worse outcome by the drivers.

Both the RDEU and the PT approach suggested in this thesis, provide insights into travellers' response to dynamic pricing that could not be captured with less complicated model structures, like the RUM-EUT model. The conceptual principles that characterise the various risky choice models have certain differences in their behavioural assumptions, and thus it is plausible that their applicability is context-specific. Moreover, it is not clear if the increased complexity from the non-linear transformations leads to improved models. As a result, a comparison of goodness-of-fit metrics follows in order to identify if there is a superior specification. These metrics are: the likelihood ratio index, the adjusted likelihood ratio index, the BIC criterion introduced in subsection 4.2.4 and the likelihood ratio test[51].

The PT models are not included in this comparison because they are non-nested, i.e. they cannot be a parametric generalisation of any of the other models. The test statistics are presented in Table 4.15.

Table 4.15: Model fit comparison for risky choice models

Models	**EUT (Linear)**	**EUT (Nonlinear)**	**RDEU (Linear)**	**RDEU (Nonlinear)**
No of parameters	19	20	20	21
Final LL	-546.489	-545.749	-545.526	-544,518
$\boldsymbol{\rho}$	0.258	0.259	0.259	**0.260**
$\bar{\boldsymbol{\rho}}$	0.232	0.231	0.232	0.232
BIC	**1225.37**	1230.86	1230.41	1235.36
LR	-	1.48	1.93	3.94

The main observation from Table 4.15 is that the RUM-RDEU model with nonlinear value function has the best model fit based on the ρ and $\bar{\rho}$ statistics while the RUM-EUT model with linear value function has the best model fit based on the BIC metric and the likelihood ratio test (the null hypothesis is not rejected for any general model at the p=0.1 significance level). However, the differences across the four models are minor.

[51] The likelihood ratio is $LR = -2\ (LL_R - LL_G)$ where LL_R is the final log-likelihood of the restricted model and LL_G is the final log-likelihood of the general model. Here the RUM-EUT model with the linear utility function is considered to be the restricted model and the other models are characterised as general since they can be reduced to the RUM-EUT model with certain restrictions on their parameters. The null hypothesis of the likelihood ratio test is that the restricted model is true, and it is rejected if $LR > \chi_a^2$ which is the critical value from the chi-squared distribution.

Looking at the aggregate statistics, 67.9% of the observed choices are in favour of the “booking now” option while, for the 32.1% of the choice situations, respondents have selected to gamble, hoping for a decrease in price. For 56.4% of the “booking now” choices, the deterministic price was lower than the expected future price, suggesting a rational riskless decision. The other 43.6% is associated with a higher likelihood for a decreased price, reflecting the risk-aversion of the individuals. Among the strategic choices, 80.9% were based on a lower expected price whereas for the 19.1% of the risk-taking situations the probability of loss was higher than the probability of gain.

Furthermore, 18.6% of the respondents have chosen the riskless option for all nine choice situations and a small percentage of 1.7% were highly risk-prone since they were always selecting the “booking later” alternative. Regarding the demographics, it is observed that older and employed individuals tend to be risk-averse while individuals that have children are more likely to be risk-prone. Comparing these characteristics with the segmentation that has been performed in the previous section, it can be hypothesised that individuals that belong to the “price-conscious” class tend to be risk-averse. Indeed, after adding the class-membership probability in the utility function of the risky choice models it was observed that there is a statistically significant positive relationship between “price-conscious” users and risk-aversion. Likewise, “time-conscious” users are more likely to choose the “book later” option, i.e. to demonstrate strategic behaviour.

The identification of myopic and strategic behaviour through the risky choices presented in this chapter is very useful for the modelling of dynamic interactions between charging service providers and EV drivers. Simultaneously, the observation that attitude towards risk varies between the two classes of drivers can be translated into a variability in booking curves for the revenue management application. In particular, since “time-conscious” users are more likely to choose the “book later” option it can be assumed that their arriving rate will increase as the end of the booking period approaches. On the same basis, “price-conscious” users are likely to arrive at the booking system with a decreasing rate since they have a higher probability of being myopic in their response to dynamic prices. The shape of the two booking curves[52] is presented in Figure 4.12.

[52] This representation is adopted from the airline revenue management literature, where the convex curve reflects the behaviour of leisure travellers and the concave curve reflects the behaviour of business travellers.

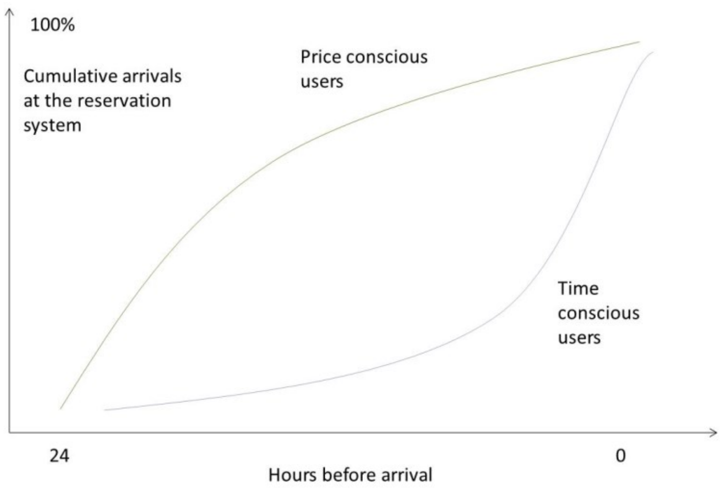

Figure 4.12: Booking curves for the heterogeneous classes of EV drivers

4.4 Summary

In this chapter, the data collected from the EV-PLACE survey and especially from the two choice experiments has been used to analyse the charging preferences of EV drivers and their response to dynamic pricing. In particular, data from the charging game was used to estimate the parameters for charging duration, charging location, travel timing and the joint price for the parking/charging bundle. On the other hand, data from the booking game was used to explain the response to dynamic pricing and identify the existence of strategic behaviour, i.e. willingness to wait for reduced future prices.

Regarding the objectives that have been set at the beginning of the chapter:

- The estimates for the charging attributes were significant and in agreement with the *a priori* expectations. Further discussion and additional data samples (ideally from revealed preferences) are required to confirm the positive coefficient for charging duration, which was found in this thesis as well as in Daina (2014). It is plausible that this is an effect of the hypothetical scenarios and a misperception that longer charging durations are associated with increased SOC, even though it was repeatedly highlighted during the instructions of the charging game. Nevertheless, if it stands for real-world applications, it gives a higher level of flexibility to the control methods applied by the charging service providers.
- The interaction terms have shown a systematic heterogeneity in taste for charging characteristics, that is explained partly from socio-demographics and revealed charging habits, and partly from scenario-based trip attributes. On the other hand, after

controlling for this systematic heterogeneity, the random residual that is captured with the mixed logit model is relatively small.

- Two segments of EV drivers were found and labelled as “price-conscious” and “time-conscious”. The probability of an individual belonging to one of these classes is partly affected by the latent construct pre-planning. Attitudes and perceptions towards pre-planning were originally investigated because of the restrictions that battery range imposes on everyday travel and because of the nature of the suggested reservation system.
- The estimates from the booking game suggested a general tendency towards risk-aversion since the majority of the respondents preferred the safe option instead of waiting for a better price. Younger, unemployed and individuals with children, i.e. those with higher probability to belong to the “time-conscious” group demonstrated an increased likelihood to be risk-averse.
- Non-expected utility approaches confirmed the existence of nonlinearity in the attitudes towards risk. Specifically, the employed weight functions suggested that individuals slightly underweight outcomes with small probabilities and overweight outcomes with high probabilities. Moreover, the prospect theoretical specification demonstrated that there is a significant difference in how EV drivers perceive gains and losses.
- Even though there is an inclination towards risk-aversion, individuals with certain characteristics were found to be strategic in their choices and this behaviour could have significant effects on the supply side and the revenue margins for charging service providers.

The heterogeneous individual preferences that were identified in this chapter are very significant both from a policy and from a business perspective. First, the need for disaggregate analysis is emphasised contrary to the aggregate charging scenarios that have been implemented until now for policy analysis. Second, the stakeholders at the lower level (charging service providers, parking operators and distribution network operators) can build better-informed models and target their services to the respective segments of the EV drivers' population. By linking the attribute valuations with personal characteristics, it is possible to impute the respective valuations for future EV drivers and enhance the CSPs' ability to implement not only dynamic pricing but personalised pricing (i.e. first-degree price discrimination) as well (Sonnier, 2014).

One limitation of the research is that the small proportion of existing EV drivers along with the difficulty in tracing them created the need for a mixed sample strategy, including individuals that do not own or lease an electric vehicle but seriously consider to purchase one in the near future. Therefore, the modelled charging behaviour might not be representative of future EV adopters. In addition, there is a possibility that the resulting sensitivities are context-specific and affected by the geographical idiosyncrasies of UK and Ireland. Their transferability to other countries is not straightforward before having a cross-examination with similar datasets collected there.

Furthermore, the screening process that was followed to select the final sample limited the respondents to 118 and the choice observations to 1062 for each of the SP exercises. Most of the produced estimates are statistically significant, but their stability is questionable especially after latent segmentation. For example, it is observed that the parameters for some of the attributes and the interaction terms become insignificant for the "time-conscious" group, which consists the minority of the EV-PLACE respondents. Future research should aim to the collection of larger datasets in order to confirm the class-specific sensitivities found here.

Putting aside the limitations above, this dissertation provides the first explicit estimates for out-of-home charging behaviour and consists an innovative study of the conjunction between EV recharging and parking choices.

The detailed demand representation achieved at this chapter is indispensable for the revenue management application that follows. At the end of Chapter 6, the researcher advises on the recommended steps for an implementation of the holistic framework in practice and highlights the essential data points that charging service providers should aim for.

5 ELECTRIC VEHICLES AND THE GRID

5.1 Overview

The operation of the power system, the security of supply to electricity end-users, as well as the revenue for operators highly depend on the ability to predict the spatiotemporal distribution of electricity demand. The additional demand from BEVs and PHEVs has the potential to create multiple challenges for electricity generators and distribution utilities. For example, a surcharge to the existing peak load will necessitate the activation of generation units that are more expensive, assuming that they are available in the first place.

The gradual transition to a more intelligent grid, with sophisticated information and communication technologies as well as the promotion of distributed generation, could facilitate the integration of EVs with the power system. This *smart grid* will enable real-time monitoring and exchange of data, giving the opportunity to operators to control more efficiently individual vehicles' charging schedules.

The smart grid is also indispensable for the realisation of the Vehicle-To-Grid concept, where the batteries of EVs can be used to store and provide electricity back to the network. As it will be described in this chapter there are several applications of V2G for different electricity markets, from peak power provision to frequency regulation.

The first section of this chapter provides a detailed presentation of the electricity market in the UK so that the various stakeholders and their roles are clearly defined. In this way, it will be easier to identify the key responsibilities of the upcoming EV players and where they should be positioned in the generation-distribution-supply map.

Subsequently, the importance of forecasting future electricity demand is highlighted. Having the ability to predict how EV charging demand is going to be dispersed in time and space, operators can implement charging coordination (or smart charging) methods in order to achieve optimal allocation. The main differences between centralised and decentralised smart charging algorithms are denoted and the characteristics of the intermediary agent who is responsible for the proper management of charging coordination (i.e. aggregator or charging service provider) are defined.

Before proceeding with the modelling framework in Chapter 6, relevant studies that investigate EV fleet management strategies are presented. Significant aspects of the research problem like the resolution of spatial price differentiation and the special features of out-of-home charging opportunities with respect to the CSP are discussed.

The first section of Chapter 5 finishes with a comparison between charging coordination modelling studies. Some of the criteria for this comparison are: the objective of the optimisation problem, the particular effect that is investigated, the assumptions about charging demand, the incorporation of V2G techniques etc. Many of the reviewed studies come from an electrical engineering background and hence the representation of travel demand or charging behaviour is quite simplistic compared to the representation of the supply side. Nevertheless, including some of the demand elements that were underlined in Chapter 2, we formed a holistic classification that stresses the added value of the demand-driven revenue management formulation of this dissertation.

The focus of the second section is revenue management and its characteristics that make it suitable for application in the electro-mobility industry. Therefore, the necessary criteria for RM implementation are outlined. Then, the complications that arise when there are multiple resources for the products/services of interest are discussed. Modelling of demand in RM problems has also evolved from the simplistic independent demand model to explicit discrete choice models that can capture the heterogeneous preferences of the customers. The latter, when applied for network RM problems, form the family of choice-based network RM problems. The Segment-based Deterministic Concave Program (SDCP) that is employed for the optimisation in Chapter 6 belongs to this family of models.

Finally, we review a few existing studies of revenue management for the parking industry, including one application for EV charging infrastructure. However, none of them treats demand in the explicit way that it is treated in the following chapter.

To sum up:

- Section 5.2 describes the effects of EV recharging on power networks and conducts a cross-comparison of modelling approaches

- Section 5.3 reviews the revenue management literature and presents the choice-based network formulations that consist the foundation of the developed optimisation problem
- Section 5.4 summarises and demonstrates the innovative parts of this thesis

5.2 The effects of electric vehicles on power networks

5.2.1 The electricity system in the UK

The electricity market in the UK consists of three stakeholders (National Grid, 2011):

- **Generators**. They produce the energy that users consume using various fuels and technologies (fossil fuels, nuclear power and renewables). Large generation is connected to the transmission network whereas small generation (or embedded generation) is directly connected to the distribution network[53].
- **Network operators** (*Transmission and Distribution*). They own and operate the grid that transfers the electricity from generators to consumers, but they are not responsible for selling it. Their income comes from charging generators and suppliers who wish to use their wires. There is one transmission system operator (*TSO, National Grid*) and 14 distribution network operators for different geographic areas of the UK.
- **Suppliers or Energy Service Providers (ESPs)**. They use the distribution network to sell electricity to end-users in domestic, commercial and industrial level. Allowing customers to select their ESP creates a highly competitive market and as a result, a wider variety of tariffs and services are promoted.

The UK electricity supply industry has been deregulated in 1990. This deregulation has motivated the development of a wholesale market and a retail market. In the wholesale market, generators, suppliers and non-physical traders (e.g. banks) sign contracts and trade short-term and long-term electricity delivery. Consumers can rarely buy electricity directly from the generator (only large end-users); therefore, they choose amongst competing suppliers in the retail market.

In the wholesale market, the greatest part of electricity trading (over 90%) happens with bilateral contracts between generators and suppliers (*Forward/Futures Market*). The contracts can have a time-window of one year ahead from delivery to one day ahead. However, there is

[53] The transmission system is a high voltage (220kV-400kV) network that runs on a national or international level, while the distribution system (400V-110kV) is connected with the transmission network and the low-voltage end customers on a regional level.

a percentage of electricity trading (3% approximately) that is usually happening anonymously during the last 24-hour period before delivery, through a computer-based system (also known as *Power Exchanges*). The role of this exchange is for stakeholders to adjust their transactions as the forecasted load is getting closer to the actual value. At least 50% of domestic bills are made of wholesale energy costs.

Electricity is sold in discrete units (half-hour "chunks" referred to as *Settlement Periods*) and all the trades must take place until the *Gate Closure,* i.e. one hour before the period of interest. Finally, 2-3% of the trading takes place after Gate Closure at real-time through the *Balancing Mechanism.* The system under which all the above trades are happening is called *British Electricity Trading Transmission Arrangement (BETTA)* (Figure 5.1).

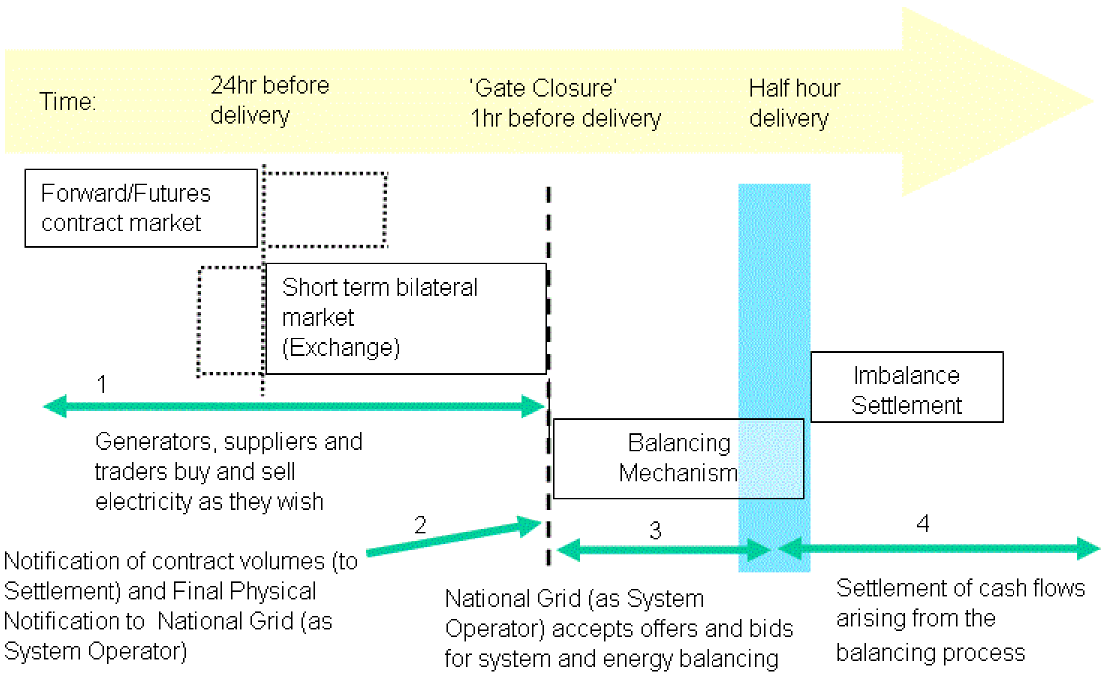

Figure 5.1: Overview of BETTA market structure. Reproduced from (National Grid, 2011)

After the actual delivery of electricity, the *Imbalance Settlement* takes place, where the system operator recovers the costs from the balancing mechanism and participants with metered electricity volumes that differ from their contracted volumes are charged with *imbalance prices*. This price depends on whether the participants are over-contracted or under-contracted and they are defined by the *imbalance costs* of the system operator. In particular, participants that produced a surplus of imbalanced energy are compensated based on the *System Sell Price (SSP),* while those that produced a deficit are charged based on the *System Buy Price (SBP).*

System stability and prevention of physical damages or electricity outages depends on the effectiveness of the balancing mechanism. Robust demand forecasts, backup generation facilities and the ability of large generators to increase or decrease their output in order to follow demand are the most crucial components. Power frequency stability is also required to preserve the reliance of the network. This can be achieved with the provision of *ancillary services* that absorb deviations of capacity from demand in real-time.

Transmission and distribution monopolies are regulated by the Office of Gas and Electricity Markets. (OFGEM). The transmission grid is a high voltage network with the responsibility to transfer electricity from the individual generator to the entry point (*Grid Supply Point*) of the distribution grid or for some exemptions, directly to the consumer. The role of the TSO, which in the case of UK is National Grid Company (NGC), is to control the balance between generated and demanded units and to take appropriate action when there is a mismatch towards any of the two sides. Also, the TSO owns the assets of the transmission network and is responsible for maintenance, investment and long-term development of the system.

Intermittent sources of generation like wind farms and photovoltaic panels (PV) complicate the balancing process because over-generation might cause constraints in the network. Both generators and suppliers should assist the TSO with its task by providing information on their output and predicted demand respectively, for half-hour trading periods also known as *Initial Physical Notifications (IPNs).* Then *Final Physical Notifications (FPNs)* should be submitted to the TSO by gate closure.

DNOs or distribution system operators (DSOs) are responsible for operating the local level distribution networks and to secure the supply at these areas. Moreover, they have to establish the costs associated with the use of the distribution network in their control area, and pass these costs to the suppliers so that they are included in the bills of end customers.

The structure of the electricity industry in England and Wales, the flow of power commodities and the various relationships between the stakeholders are depicted in Figure 5.2.

5.2.2 Forecasting of electricity

Forecasting and especially short-term forecasting is an indispensable component of the electricity trading market. Some areas of activity that are based on robust load predictions are the following: scheduling of oil purchase, scheduling of power generation, planning of energy transactions and assessment of system safety (Tzafestas and Tzafestas, 2001). In the same study, the typical time-window targets for electricity forecasting are identified:

- Half-hour ahead forecast
- One-our ahead forecast
- 24-hour ahead forecast
- Peak-load forecast over 24-hours period
- Peak-load forecast over a 1-week period
- Total daily energy consumption

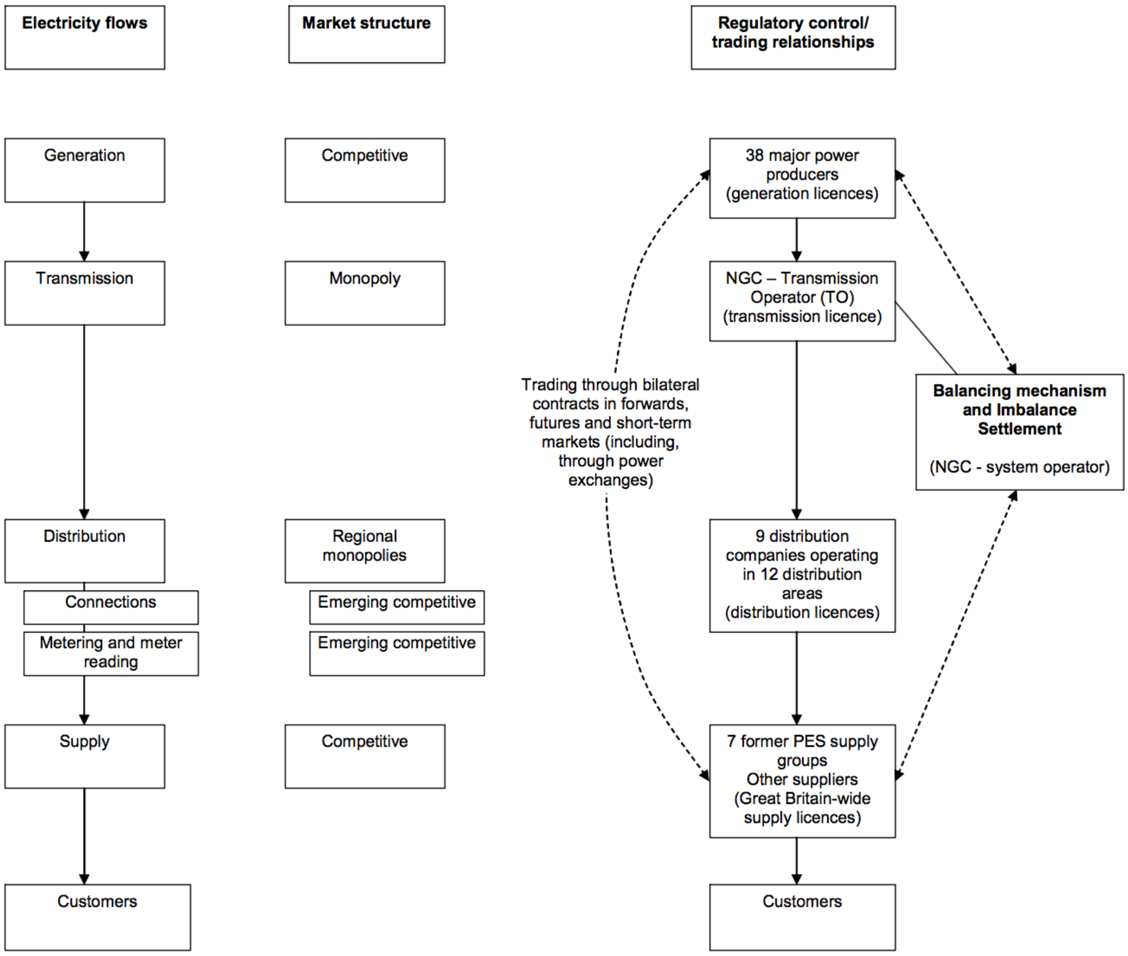

Figure 5.2: Structure of the electricity industry in England and Wales and relationships between the stakeholders. Reproduced from (Simmonds, 2002)

Electricity demand can vary throughout the day, week and year. During the day, the fluctuation follows customers' routines (washing, cooking, watching television etc.) whereas in the annual distribution higher demands are observed for the winter months. In the balancing mechanism, there is always some generation reserve that is consumed when the predicted demand is underestimated. In order to minimise this generation reserve, stakeholders must increase the confidence level of their predictions (Charytoniuk and Chen, 2000).

Several parameters should be considered as exogenous factors that affect the amount of generated electricity like weather and social variables. The main modelling techniques that have been developed for short-term electricity load forecasting are: parametric (e.g. ARMA, Fourier series etc.), non-parametric (from historical data) and artificial intelligence based (e.g. neural networks). A comprehensive review of the application of neural networks in short-term load forecasting is presented in Hippert et al. (2001).

However, forecasting methods that treat explicitly the disaggregate preferences for energy services are rarely encountered in the literature. One example is the study from Revelt and Train (1998) that apply a mixed logit specification to identify the heterogeneous household-specific tastes for appliance efficiency level.

The discrete choice methodology that was presented in Chapter 4 could provide a meaningful basis for prediction of future electricity use for EV recharging. On top of modelling energy demand based on individual preferences, this is one of the first approaches to express the consumption of electricity indirectly, through the participation in out-of-home daily activities. The suitability of applying activity-based methods to model urban resource demand (like electricity and gas) at high resolution was demonstrated in Keirstad and Sivakumar (2012). Obviously, behavioural changes as the pool of EV drivers evolves are anticipated and should be further explored to improve the quality of the prediction model.

5.2.3 Smart Grid and Smart Charging

The main purpose of a power system is to distribute power from the generator to the physical places of demand. The need to charge BEVs and PHEVs will increase the demand for electricity and, taking into account that recharging is dynamic in time and space, this might cause delivery problems especially during peak periods. This multi-dimensional problem can be tackled with the deployment of smart grid. Smart grid is combining advanced sensors with communication and control methods, offering a more distributed approach both in the transmission and the distribution level and adding intelligence to the system.

It is anticipated that the distribution network will benefit more from the new technology because it is relatively passive at the time being (minimal communication and control) compared to the transmission network (Houses of Parliament, 2011). Some of the critical advantages of the smart grid are: self-healing, real-time monitoring, bidirectional exchange of information, economic benefits for suppliers and consumers, lower peak demand, improved security, power quality, multiple generation and storage options and efficient operation (Fang et al., 2012).

The main modelling approach for smart grid environments in the power networks literature is the employment of Multi-Agent Systems (MAS). For example, Karnouskos and de Holanda (2010) have simulated a smart grid city where discrete heterogeneous devices of energy production/consumption act as autonomous agents with social characteristics. Households, appliances, vehicles, power stations and interconnections between cities are some of the simulated entities. According to Vandael et al. (2011), the key benefits from using MAS in this area are: flexibility, extensibility and fault tolerance.

There are several ways that the simultaneous recharging of electric vehicles can be achieved both from an energy capacity and a communication perspective. A basic classification is the following: (Waraich et al., 2013):

- **Dumb charging**. BEVs and PHEVs start to charge immediately after they are parked and plugged-in, aiming to fully recharge the battery. In this case, electricity price usually remains constant for the whole day.
- **Dual Tariff Charging/Time Of Use (TOU) pricing**. In order to shift behaviour so that people consume electricity overnight when the demand is low, there is a differentiation between low price during the night and high price for the rest of the day. TOU pricing can influence EV users' travel behaviour and activity scheduling.
- **Smart Charging**. This is the scheduling of EV charging profiles in order to accomplish technical and economic targets for drivers and operators. It can be modelled with optimisation techniques or heuristics and it can have several objectives that are described thoroughly in the next subsection. Smart charging can take the form of centralised smart charging or decentralised smart charging
    - *Centralised smart charging or direct control.* Plugged-in vehicles transmit information about their parking duration and the required SOC and a central entity decides when to charge them and when to use the vehicles for energy storage in the case of V2G (Acha et al., 2010; Clement-Nyns et al., 2009; Galus et al., 2012). Then the charging or discharging rate information is transmitted back to the charger/inverter of the EV through the vehicle controller.
    - *Decentralised smart charging.* The supplier provides the spatiotemporal distribution of electricity price and a smart in-vehicle device controls the

charging intervals of the electric car (Pecas Lopes et al., 2009; Schieffer, 2011; Waraich et al., 2013).

Centralised smart charging reaches an optimal solution but at a high communication cost in order to manage all EVs concurrently, in contrast to decentralised smart charging which reaches a less than optimal solution but at a lower communication cost (García-Villalobos et al., 2014).

The goal of centralised market mechanisms, in general, is to reach a market clearance or maximise the social welfare. One main disadvantage is that the characteristics of the demand side (habits, preferences etc.) would be reflected on their bids, hence raising privacy issues. On the other hand, decentralised approaches like dynamic pricing do not raise privacy concerns, since they do not require from individual customers to reveal personal information to a central entity. If dynamic prices are pre-determined, they do not capture real-time demand and hence, the market outcomes can be rather inefficient (Kirschen et al., 2000).

Detailed reviews of PHEV integration with smart grids are presented in Green et al. (2011) and in Hota et al. (2014). According to the authors of the second study, there are four main domains that need to be analysed through further research:

- Charging control/scheduling of PHEVs
- Integration with renewable energy sources
- Vehicle participation in electricity markets
- Smart parking and infrastructure requirements

The analysis in Chapter 6 is oriented around the first and the fourth domain and, therefore, the relative studies are cited later in this chapter.

Su et al. (2012) highlight the multidimensionality of the EV grid integration problem by indicating the following aspects that should be jointly considered with power system analysis: technology, policy, environment, economy, social impact and transportation. Moreover, they develop an analytical framework for the combination of power and transportation systems. In this framework, the distribution system is modelled with OpenDSS (an open source simulator) (Taylor et al., 2010) while the transportation system is represented as a combination of data estimation (i.e. vehicle range, charging rates and EV penetration level) and dynamic traffic micro-simulation (i.e. driving and parking patterns with DYNASMART) (DYNASMART-P, 2007).

5.2.3.1 Smart meters and Demand Side Management

The proper function of a smart charging system relies on smart metering. Recharging prices are displayed on the smart meter and users choose whether they should charge or postpone the charging event in the expectation of lower tariffs. For example, when there is a peak in electricity demand, prices might be prohibitive for recharging an EV and thus signals on smart meters can shift this demand to another time of the day.

The concept of attempting to affect consumer behaviour in order to smooth the electricity base load and avoid congestion is called *Demand Side Management (DSM)*. DSM has several additional benefits for the power grid, including the ability to reduce the cost of electricity generation and to improve the investments for transmission and distribution networks (Strbac, 2008). In particular:

- Adverse weather conditions or breakdowns in the *generation* system could lead to infrequent electricity shortages. The long-term reserve that is required in this case could be dealt with the installation of generation units that would be turned-off most of the time. With DSM it's possible to compensate some households for forgoing consumption during the constrained periods. Assuming that these units are gas-fired-type plants, the investment savings from DSM would start from £250-£400/kW and grow considerably for unexpected costs in the planning process of the construction.
- DSM also allows the implementation of corrective actions, like curtailing some electricity loads at problematic locations. The value of DSM, in this case, depends on the *transmission* capacity (system stress), which can be enlarged with the installation of renewable generation. In the UK, savings from avoiding the reinforcement of the transmission network are estimated to be £300/MW km and they are likely to increase with complications in the planning period.
- The cost reductions for the distribution network are not so well quantified but some of the DSM benefits are the improvement of transformers' loading capabilities and the facilitation of connecting distributed generation.

Moreover, DSM can lead to savings for the electricity bills of end-users (Albadi and El-Saadany, 2008).

Assuming that the charging point is equipped with the appropriate technology, smart meters can function automatically and interrupt the charging process based on the price signal. Furthermore, smart meters offer a higher level of visibility of the distribution network and allow the DNOs to better manage the distribution assets. In this way, DNOs achieve their target of minimising electricity losses across the network and they increase their efficiency in detecting and fixing outages in the distribution system. The problem in the UK is that DNOs, unlike suppliers, have an indirect relationship with the end-users. Thus, there must be some modifications in the connection between suppliers and DNOs, so that the latter can have access to individual smart meters.

5.2.3.2 Aggregator/ Charging service provider

The problem described above could be solved with the introduction of an intermediate unit that would aggregate the information from multiple EVs and manage them in real-time. This intermediate unit often referred to as aggregator, can work as an interface between the different players in an electricity market and it can give visibility to electric vehicles and their integration with the power network. Moreover, the aggregator or Charging Service Provider has to satisfy the target State Of Charge (SOC) for each EV individually and optimise the charging activities subject to the local grid constraints (Sundstrom and Binding, 2011). However, its role is restricted by the flexibility in drivers' preferences and hence their willingness to adjust their charging behaviour. For decentralised smart charging, it is possible that the role of the aggregator is undertaken by the electricity retailer.

In addition to controlling the charging process, the aggregator is also responsible for the participation of EVs in the electricity market. Robust techniques are required to predict charging profiles and communicate them with the DSO. After the initial agreement with the DSO, if there is no compromise for the regional low-voltage network, the aggregator could enter the power negotiation by placing bids in the day-ahead electricity market. Consecutively, a second agreement is required, this time from the TSO, or a request for changes in the predicted demand profile if it is not satisfying the transmission network constraints. With the cooperation of the TSO the aggregator could also take part in the ancillary services market.

Existing electricity markets will be transformed in order to accommodate the charging demand and the necessary charging services. New agents that will play significant roles in these transformed markets are (San Román et al., 2011):

- EV owners
- EV suppliers-aggregators (EVSAs) who are the retailers that will provide electricity to the owners in a competitive environment

- Charging Point Managers (CPMs) who can be the owners for home recharging or other agents for out-of-home based facilities (as long as they are qualified by the law to resell electricity to third parties)

The aggregator could be any of the last two agents or a conventional electricity supplier. CPMs in commercial or office buildings could install independent EV metering devices (EVMs) for charging posts if they want to bill charging services[54]. Moreover, they are responsible for the operation and maintenance of charging infrastructure.

For public places, EV drivers would have contractual relationships with an EVSA (either the same one that bills them for electricity use at home or another one) while the EVSA would pay the DSO for the regulatory expenses. For privately owned facilities, the CPM would buy the required electricity from a supplier who, in turn, would have to pay the regulatory charges to the DSO. The profitability for the CPM would depend on the ability to sell services that are differentiated from home charging or charging at public places. Despite CPMs and EVSAs operating in a competitive market, their ability to set EV charging prices should be authorised and regulated, as it is the case for conventional electricity suppliers.

For centralised smart charging, the CSP needs to process four inputs before implementing any control algorithm: the driving patterns[55] of the EV owners, the battery model of the vehicle (e.g. SOC fluctuations[56] and level of degradation), the grid constraints (both for high and low-voltage networks) and finally the characteristics of the electricity markets (day-ahead prices, prices for regulation up and regulation down etc.)

5.2.4 Fleet management techniques

The effects of BEVs and PHEVs charging on the grid have already been investigated in several studies coming from various research fields like electrical engineering, economics and information systems. Researchers have explored the implications for the distribution grid and the areas that are more prone to bottlenecks (Pecas Lopes et al., 2009; van Vliet et al., 2011; Flath et al., 2013; Stoeckl et al., 2011), the effects on the life-cycle of distribution transformers

[54] EVMs could be embedded in the vehicles. They should also be standardised along with charging infrastructure and integrated with open communication architectures in order to ensure interoperability, information exchange and accessibility to manufacturers.

[55] For the majority of the studies in this area it is assumed that the CSP has complete information of the driving patterns. Stochastic approaches that try to capture the uncertainty in the demand parameters can be also found in the literature. Typical examples are Monte-Carlo simulations or probabilistic distributions for parking times and initial SOC.

[56] Typically this is modelled as an individual battery pack and the performance of SOC is based on linear and nonlinear approximations.

(Roe et al., 2009), on generation profiles (Schneider et al., 2008), on high and medium voltage grids (Hadley, 2007) and on pollutants (Roe et al. 2009), while others (Letendre and Watts, 2009) tried to predict the potential number of vehicles that could be accommodated by smart grids.

Previous simulation studies have shown that bottlenecks can be caused by penetration levels in the range of 10%-40% (Flath et al., 2012). Areas with increased number of EVs are susceptible to additional power quality problems like transformer overloads, branch congestions, voltage deviations, power losses or transformer degeneration. Most of these problems are due to the limiting capacities of local substations and the purpose of the developed framework in this dissertation is to evaluate the maximum revenue that charging service providers can achieve under this constraint.

In order to address the above problems, one way is to reinforce the grid, which requires substantial investments and does not tackle the environmental issues related to power generation. Also, energy suppliers will need to prepare for the additional charging demand with its uncertain temporal distribution. Improvements of metering and administrative services are necessary in order to cover the needs of the new "mobile" energy loads.

The application of coordinated charging strategies (Rahman and Shrestha, 1993; Richardson et al., 2010) should be integrated with future policies and business models for electric vehicles. Apart from preventing local power constraints, charging coordination is useful to balance demand and supply of electricity at an aggregate level. Basically, most researchers focus on the aggregated problem, while only a few look into the local network constraints (Clement-Nyns et al., 2009; Pecas Lopes et al. 2009; Flath et al., 2012; Flath et al., 2013). In any case, there are two components of interest for an operator: the price charged for electricity, and the required charging power.

Apart from mitigating the negative effects of EV clusters, charging coordination can function beneficially in other ways. For example, low-load conditions during overnight off-peak periods lead to significantly increased prices for regulation down services. Shifting charging events to these periods, not only increases the load but also decreases the costs from turning off generation units that are under-utilised. Moreover, EV batteries have fast response capabilities that are ideal for daytime regulation services.

Schieffer (2011) has investigated a decentralised charging approach along with V2G applications and emphasised the importance of a system global optimum through the load flattening effect (Figure 5.3). The homogeneous distribution with valley filling (or load levelization) requires a higher but stable electricity generation, which minimises the needs for regulation and can be managed more easily.

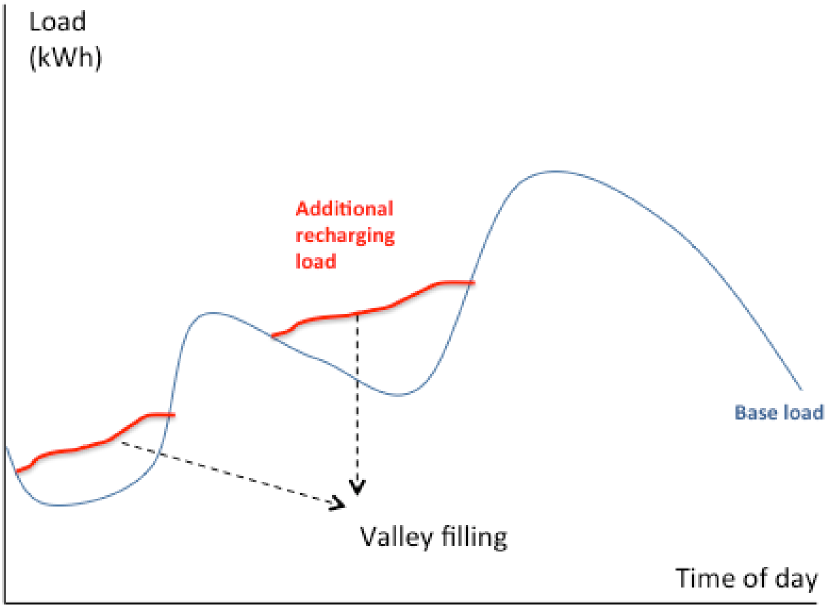

Figure 5.3: Load flattening effect

As it was explained in Chapter 2, the demand for electricity in most of these studies was based on fixed, exogenous assumptions for daily schedules, travel times and dwelling periods.

5.2.4.1 Control for spatiotemporal demand

Schweppe et al. (1988) were the first to suggest that the value of electricity, as a commodity, should be differentiated in two dimensions: time and space. The application of DSM depends on the transformation of demand from fixed to flexible.

Electric vehicles retain a high flexibility potential due to their storage capability and their mobility potential. Papadaskalopoulos and Strbac (2011) present a decentralised mechanism with EVs that is based on Lagrangian Relaxation (LR) methods. In particular, sub-problems are solved for each consumer and generator, while in a global level prices are updated so that system constraints are satisfied within some tolerance. EVs participating in this decentralised mechanism are characterised by non-convexities due to inter-temporal preferences and constraints. As a result, it is difficult to find an equilibrium solution, but this is treated with the application of LR-heuristics. Demand is fixed after a threshold is satisfied and the problem is transformed to economic dispatch for generators.

In a subsequent study, the authors extend their framework by taking into account transmission network constraints (Papadaskalopoulos and Strbac, 2012). Flexible EV loads diminish the locational price differentials that are caused by network congestion and improve economic implications like congestion surplus. The economic dispatch problem that was created with the LR-heuristic is transformed here to an optimal power flow model.

Temporal pricing is common and its purpose is to reflect the current cost of generation. In practice, the market-clearing price for all operating generators is determined by the generator with the highest marginal cost (Flath et al., 2013). The cost of generation is usually higher during periods of peak demand and this could be transferred in charging prices for EVs. On the other hand, the costs of transmission and distribution networks can be conveyed through the spatial dimension of pricing.

When the purpose of decentralised control for EVs is to optimise the operation of the local distribution network and to avoid congestion and overloads of local substations, then there is an important relationship with the spatial distribution of demand. Locational differentiation of electricity tariffs would reduce the distributional network investments at the first place, and then it would allow behavioural changes steering system participants to low energy demand areas (Strbac and Mutale, 2005; OFGEM, 2009). In practice, locational pricing is applied in a nodal level (transmission grid level) and this is known as Locational Marginal Pricing (LMP) but there is not a lot of differentiation in the distributional level, mainly because of the "deep" connection charges[57] required to send the locational signal (Brandstätt et al., 2011). The complexity of nodal pricing for the customer side is another restricting parameter and an intermediate solution is zonal pricing. The zones where price can fluctuate are either predetermined or dynamically modified based on network conditions and this strategy is equivalent to congestion pricing on road traffic systems.

The purpose of the activity at charging locations is a quite significant factor when analysing the effects of EVs on low-voltage networks and the implications for charging coordination. Several simulation studies have used daily activity data to create spatial clusters of charging demand (i.e. residential or industrial areas) and investigate the grid performance within these zones (Rahman and Shrestha, 1993; Waraich et al., 2013; Flath et al., 2013).

In terms of results, as it was indicated in Chapter 2, dual-tariff or off-peak strategies have the side effect of shifting spikes to the low-cost periods. Irrespective to the charging strategies

[57] Shallow connection charges reflect only the direct cost of the connection and the relative assets. Deep connection charges express the costs for reinforcements deeper in the network and they are necessary for locational pricing because they reflect the impact of a connection. One of the reasons that it is difficult to implement deep connection charges is the ambiguity in allocating the costs to more than one user.

applied, load spikes from EV charging in an aggregate level typically occur with time-of-use price-based coordination methods (Flath et al. 2013; Rahman and Shrestha, 1993). However, Flath et al. (2013) found that these spikes can be mitigated with the addition of a spatial factor to the electricity price, which would take into account the local capacity constraints.

The digitalization of the grid created new opportunities for customer-centric management of EV charging demand. The provision of tailored electricity services to specific customer segments based on their energy consumption patterns (Giordano and Fulli, 2012) would help the energy suppliers and DNOs to manage demand in a sustainable way and at the same time to encourage behavioural shifts when they are needed.

5.2.4.2 Out-of-home charging coordination

Coordination of plugged-in EVs is a challenging task for public or private parking operators and for all types of facilities that provide parking places (e.g. park and ride stations, shopping malls etc.). Lack of familiarity with the new technology can complicate the management of charging infrastructure by parking operators, resulting in the emergence of an intermediate agent who would be contracted to carry out this task. This agent could be an EVSA, or otherwise, the parking operator could act as a CPM.

The new EV-related agents will increase the complexity concerning the stakeholders' responsibility (and authorization) to provide charging services. In privately owned parking facilities, the CPM should be responsible for the operation while for on-street public places it could be an extra task for the DSO. The CSP functions as a bridge between electricity market players and individual EVs (Bessa and Matos, 2012). For example, in London, there is a contractual relationship between Source London and four CSPs: ChargeMaster, PodPoint, Elektromotive and CPMS. Therefore, different charging posts are owned and operated by different CSPs and the commercial agreements for future applications of demand control have to be investigated by the DSO, i.e. UK Power Networks.

Out-of-home recharging generates an additional role for a charging service provider, this of revenue optimiser for the collaborating parking facilities. A schematic presentation of the interactions between CSP, DSO, drivers and parking operators in order to accommodate out-of-home charging activities is demonstrated in Chapter 6.

5.2.5 Vehicle-to-Grid applications

In some cases, bidirectional power flow allows the electric vehicles to inject electricity back to the grid, commonly known as *discharging mode*. This concept of Vehicle-to-Grid (V2G) can be considered as an extension of smart charging where vehicles are transformed in distributed generators or storage devices (Kempton and Tomic, 2005a). The first system that enabled an electric car to offer V2G services has been designed by AC Propulsion of California and it was reported to have "zero incremental cost" (Letendre and Kempton, 2002).

V2G allows vehicles to become revenue assets where income depends on factors like battery size, dwelling periods and service pricing. It also gives the potential for a 20% reduction in the demand for generation capacity by 2050. This capability saves utilities from the high costs of regulating the generation facilities, which in the U.S. is approximated to $4,000 per year. Two main drawbacks with V2G operations are: a) the faster degradation of the battery and b) the increased energy losses.

The areas where V2G can fit with the electricity market and the degree of its suitability are cited below (Kempton and Tomic, 2005b):

- **Base load power**. The common all-day generation process. *Low suitability* because it results in a high cost per kWh.
- **Peak power**. Periods where load profiles are anticipated to reach their maximum. Aggregated EVs allow significant delays in the start-up of cycling or peaking units *Suitable in some cases*.
- **Spinning reserves**. Fast-response reserve units for extreme cases of malfunctions and blackouts. *Competing solution*.
- **Regulation**. Maintenance of system frequency[58] and supply at a steady level and control of either supply or demand when they deviate from this level. These services take place in a local scale, but they have an effect on the entire grid. V2G is *highly competitive* here.
- **Storage** of surplus energy from intermittent renewable energy. Peaks and valleys from renewable sources could be significantly smoothed. This is mainly beneficial for wind energy, which in many areas peaks during the low-demand overnight periods. *High suitability* for V2G especially in the long term.

Guille and Gross (2009) were the first to present a conceptual framework for the integration of V2G services with existing power systems in an operational and planning level. One of the challenges discussed in this framework is the incentive program that needs to be designed so

[58] Frequency fluctuations are monitored every 2-4s and a positive value requires the frequency to be lowered (regulation down) by reducing the generation outputs from units participating in regulation services. For a negative value the exact opposite action is required, i.e. a rise of the generation output (regulation up).

that EV owners participate in the aggregation. They suggest the creation of a *package deal* where individuals are awarded for long-term commitments (e.g. discounts for battery maintenance, charging or parking) and penalised if they fail to meet the obligations of their agreement with the aggregator. Services for battery maintenance, for example, could ease some concerns of the EV owners regarding the degradation of the battery from V2G. Similar "packages" could attract a substantial aggregation of vehicles for the operator. For frequency regulation, EV drivers could be paid even when the vehicle is idle, just for providing the availability of V2G services.

Communication and control are the first priorities for V2G applications and researchers are principally aiming to decentralised systems where the decisions are made by the vehicle owner, and control is directed via wireless networks. Kempton and Letendre (1997) have proposed a control panel that is installed onboard and provides drivers with information on the real-time electricity price and gives suggestions for charging timings. For this reason, users must be fully informed to compare the utility they gain from the selling prices with the disutility from the battery degradation by the charging-discharging cycles.

Both for centralised and decentralised systems, the CSP will need to aggregate the information from individual charging events and present the total figure to the TSO (Kamboj et al., 2011). TSO has a minimum requirement of power provision to the grid in order for the interested party to participate in the electricity market. Thus, the inability of an individual electric vehicle to reach this minimum requirement makes the role of the CSP indispensable for V2G applications.

The TSO needs to deal with predictable and reliable suppliers and a single EV cannot guarantee this reliability because of the dynamic character of its charging schedule. However, this is not a problem when controlling a cluster of EVs and the individual uncertainties cancel out each other. In terms of frequency regulation, the bids between the grid operator and generators are in the scale of MW while the battery of a single vehicle can provide power capacity around 20kW. The aggregated vehicles can have two roles: this of a *controllable load* and this of a *generation/storage device.* In a smart grid environment, the flows between vehicles and suppliers have two layers: a physical layer (e.g. energy, power, parking services etc.) and a communication layer (e.g. information, monitoring, billing data etc.) (Figure 5.4).

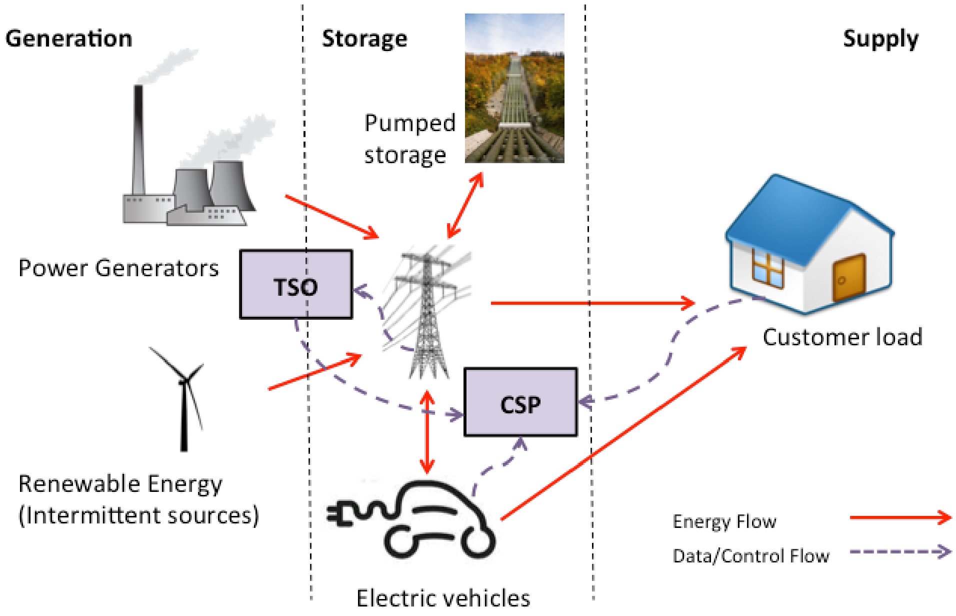

Figure 5.4: Vehicle-to-Grid (V2G) and Vehicle-To-Home (V2H) in a smart grid environment

If the cumulative battery capacity of the EVs that are connected to the grid reaches a significant size in MW, there is a higher likelihood that large industrial customers will buy V2G services. Therefore, collective action is beneficial for individual drivers who will get compensated for selling the energy stored in their vehicles.

In frequency regulation, the primary goal of an aggregator is to maximise its revenue, i.e. to provide as much power capacity as possible when the regulation price is high so that the payment from the system operator is maximised. As it is expected, this goal is constrained by the energy limits of the EV battery (lowest and highest SOC). Moreover, early departures of EV drivers that do not abide by their plug-in "agreements" could cause significant deviations both in power delivery and in revenue performance. However, for an increasing amount of vehicles participating in regulation, the effect of this behavioural uncertainty decreases.

5.2.6 Modelling approaches

One necessary input for decentralised smart charging is the daily distribution of the electrical energy that is available for EV recharging. This distribution, which differs across geographical regions, will define the price signals that are sent to the drivers. The energy availability at a distribution feeder level can be deduced from the existing demand for electricity that is known to the utility operator. There are two possible ways to obtain this information: either to infer it from sub-station measurements or directly collect data from customer meter readings (Schneider et al., 2008).

Waraich et al. (2013) developed an integrated power and traffic simulation platform where the activities of individual agents in the city of Zurich were modelled to examine the spatiotemporal effects on the electricity network. The energy demand for specific areas (e.g. residential, industrial etc.) is modelled based on real base load curves. Also, a PEV managing device is responsible for the optimisation of the EV fleet for each area by transmitting a price signal according to the level of congestion. Typically, smart charging studies assume schemes of real-time electricity pricing and that EV drivers fully participate at these schemes.

Ma et al. (2010) present a decentralised charging coordination approach where price signals are influenced by the base load of electricity and the aggregate demand for EV recharging. Each individual vehicle has its own local controller, which is affected by the average charging strategy of the EV population. The authors suggest that the final combination of schedules for the local controllers converges to a unique Nash equilibrium. This equilibrium is an optimal "valley-filling" strategy that shifts charging demand to off-peak night intervals where generation costs are lower.

On the other hand, Mets et al. (2010) presented a centralised approach where the objectives were to minimise peak load and flatten the load curve. The control algorithms were based on quadratic programming and they were compared with an uncontrolled scenario where EVs were recharged with a constant rate. Sortomme et al. (2011) employ a charging coordination method for PHEVs, aiming to minimise losses in the distribution system. Their formulation is convex and thus, the optimised metrics (load factors and load variances) can be included as constraints in optimisation problems with other objectives, like revenue maximisation for the aggregator.

When V2G services are provided, operators should offer drivers the possibility, at any time, to change from discharging to charging mode so that the required SOC for their travel needs is available. These sudden changes of operation modes will most likely introduce some uncertainty in power systems planning.

In their conceptual framework for the integration of PHEVs in power systems, Galus et al. (2010) assume three states for battery level (Decreasing, increasing, staying constant) and three operational types (Uncontrolled, Controlled, V2G) and they demonstrate how transitions in these two dimensions are made (Figure 5.5). They investigate the case for PHEVs, but this figure should be identical for BEVs.

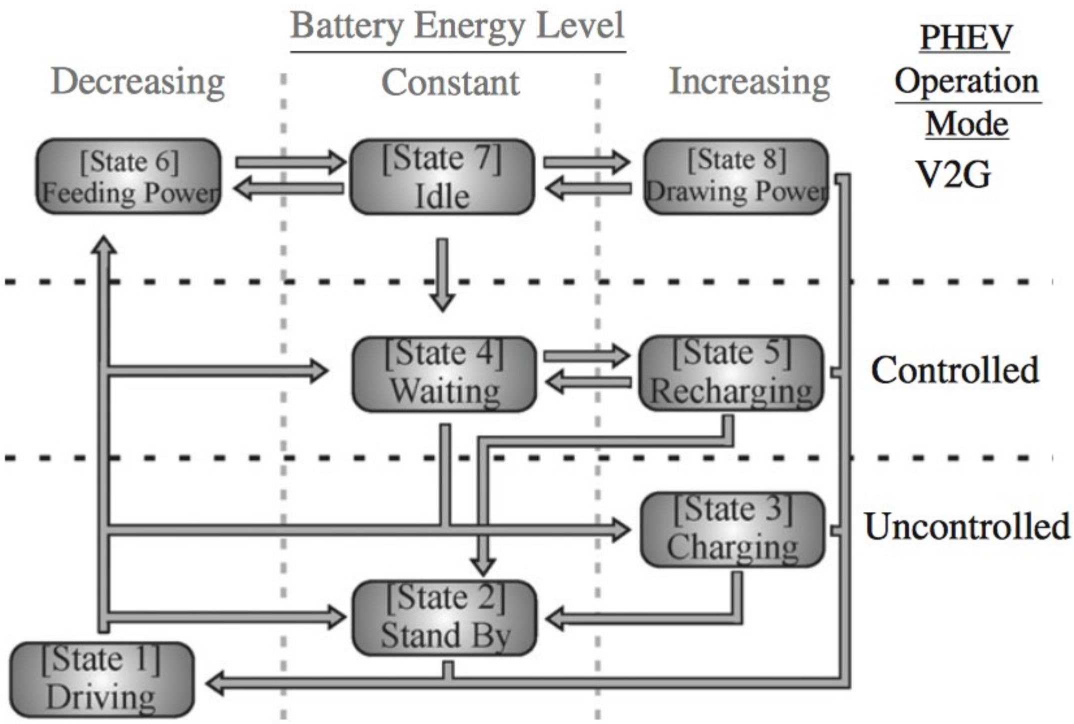

Figure 5.5: Interrelationship of operational control methods and battery states for electric vehicles. Reproduced from (Galus et al., 2010). This image has been reproduced with the permission of the rights holder, Elsevier.

The driving state in this figure is only associated with the transport network, yet it strongly affects charging coordination because it is the main activity that leads to all possible different states. For an uncontrolled scenario, the energy loads are completely defined by the stochastic (and as it is highlighted in this thesis, choice-driven) plug-in events. For the controlled scenario, the main difference is the existence of an intelligent communication system as well as some sort of contractual agreement between the driver and the operator. A transition from a controlled to an uncontrolled state (State 4 to State 3), if allowed by the agreement terms, is very useful in case an individual needs to re-schedule his activities and leave the charging location before the pre-planned departure time. The objectives for the V2G mode are not yet clearly defined in the literature. For example, it could fit in one of the five energy market areas, mentioned in 5.2.5.

In the same study, simulations are made for four nodes and a device that manages PHEVs at each node. Also, the charging decisions for the controlled scenario are not price-dependent, i.e. drivers try to recharge as soon as they plug-in their vehicles. In V2G mode, the aggregated fleet is simulated for load frequency control, with individual EVs transitioning from charging to discharging state and vice versa, according to the balance of supply and demand in the power system.

The vital role of V2G in deploying renewable sources as part of the national energy mix is discussed in Lund and Kempton (2008). Their analysis is undertaken with the use of EnergyPLAN, an energy system simulation tool while driving patterns are based on Danish mobility statistics. The impact of EVs is assessed for all the possible integration levels of wind power (i.e. 0%-100% of the total electricity demand). Their simulations suggest that smart charging (even in the basic form of night charging) leads towards a more sustainable utilisation of energy in a national level, with significant reductions in CO_2 emissions.

He et al. (2012) model the coordination for the bi-directional flow of electricity from the grid to the vehicle and vice versa, both with a global and a local scheduling approach. Their optimisation is based on real-time pricing for a small geographic area and they assume that there is no locational variation in prices. The objective is to minimise the total charging cost for the examined EVs. The cost of charging for a specific interval is positive if the energy that is directed to the vehicle is higher than the energy directed to the grid and negative otherwise. This resembles the negative prices that are adopted for V2G services in Chapter 6. This study also models the cost of battery degradation both through the total amount of energy flows, and the amount of fluctuations from charging to discharging modes.

The control algorithms in Rotering and Ilic (2011) are based on forecasts of future electricity prices and charging schedules are optimised individually for each vehicle with respect to maximising the profit (or minimising the cost) for the owner. Two optimisations are taking place: one without V2G availability where the objective is to optimise charging time and the delivered energy, and one with V2G availability where the owner can also generate profit from participating in ancillary markets. The problem is solved with dynamic programming techniques and the authors demonstrate the benefits of smart charging and V2G in daily costs for the individual.

The impact that EVs have on the grid, taking into account their storage capability with V2G services, is also assessed in Hartmann and Özdemir (2011). Average driving characteristics and activity types are adopted from German mobility data in order to simulate the number of trips that take place throughout a typical day. Three storage utilisation scenarios were evaluated: unmanaged charging (no V2G), grid-stabilising strategy (trying to reduce the fluctuations of the grid), and profit-maximising strategy (drivers try to optimise their revenue by participating in the power stock exchange). Based on the last utilisation scenario, they have demonstrated that EV drivers can gain up to 0.68 Euros/day and at the same time the fluctuations of the grid can be reduced by 12%.

In Hutson et al. (2008) the objective of their EV scheduling is similar to the present dissertation. EV drivers have to decide if they want to buy (charge) energy from the grid or sell (V2G) energy to the grid, and a particle swarm optimisation (PSO) algorithm is applied to find the optimal selling and buying periods throughout the day so that revenue is maximised for the parking lot. Another study where V2G scheduling is optimised for parking lots is this of Saber and Venayagamoorthy (2009). The coordination of charging/discharging states of EVs is modelled as a Unit Commitment (UC) problem with PSO. The objective of the optimisation is to minimise the charging cost for EV drivers.

Mirzaei et al. (2014) optimise charging coordination with the objective to satisfy vehicle drivers and the parking operator concurrently. The parking operator aims to maximise daily income while an individual driver aims to minimise the costs associated with lost opportunities and the failure to achieve the requested SOC. The income for the parking lot is a percentage of the profit from the power exchanges between EV drivers and the DSO. The authors assume that there is a reservation system, similar to this thesis, where drivers submit their preferences via cell phone or Internet applications. Another similarity is that they model the financial interactions of the operator both with the vehicle owners and the DSO. However, they do not explicitly treat charging demand and they ignore customer-side uncertainties.

Likewise, Su and Chow (2010) employ a simulator to investigate the application of DSM strategies in a municipal parking deck with multiple PHEVs. This multi-agent simulator consists of three components: the power grid, the Intelligent Energy Management System (iEMS) and the PHEVs and it allows modelling of energy prices and individual preferences. Three pricing strategies are considered: dynamic pricing, TOU tariffs and an Emergency Demand Response Program, where high economic incentives are offered in order to avoid overloads in peak periods. Their control algorithm is based on fuzzy logic and the uncertain demand inputs are treated with Monte Carlo simulation.

One interesting study where the objective of charging control is revenue maximisation for the aggregator is this of Han et al. (2010). Nevertheless, contrary to the present thesis, it focuses on frequency regulation services with the use of V2G. Methodologically, coordination of charging rates and sequences is achieved with dynamic programming while optimality is evaluated with simulations.

The physical limitations that are imposed by the distribution network constrain the power that is allocated to the available charging posts below a certain threshold. As a result, the local *substation* can use only this limited amount of remaining power to allocate to the EV customers that are connected the grid (Vasirani and Ossowski, 2013). The authors in this study develop an allocation algorithm based on a weighted measure of efficiency and fairness[59], trying to achieve the optimal balance between the two. Their optimisation is inspired by lottery scheduling methods in stochastic game theory.

There is a very rich literature in charging coordination and many different approaches to treating the problem. Some examples of the optimisation objectives that have been examined include:

- Market clearance (Papadaskalopoulos and Strbac, 2011, 2012)
- Minimisation of power losses (Clement-Nyns et al. 2009; Sortomme et al., 2011)
- Minimisation of system operation costs (Goeransson, 2010; Gonzalez Vaya and Andersson, 2012; Aunedi and Strbac, 2013)
- Minimisation of generation costs (Valentine et al., 2011; Ma et al., 2010)
- Maximisation of vehicle integration (Pecas Lopes et al., 2009)
- Minimisation of cost for power supplier (Sioshansi et al., 2010)
- Minimisation of cost (or maximisation of utility) for individual EV drivers (Dietz et al., 2011; Sioshansi et al., 2010; Galus et al., 2010; Galus and Andersson, 2008; He et al., 2012; Saber and Venayagamoorthy (2009); Rotering and Ilic (2011).)
- Balancing demand with intermittent renewable generation sources (Clement-Nyns et al., 2011; Caramanis and Foster, 2009).
- Minimisation of deviation between predicted and observed charging demand (Soares et al., 2014).
- Maximisation of revenue for aggregator (Han et al., 2010)
- Multiple objectives (Zakariazadeh et al. 2014; Acha et al. 2010; Su and Chow, 2010).

From an economic optimisation perspective (cost for drivers), optimal smart charging is usually modelled as a linear program with certain limitations. One limitation is the assumption of perfect knowledge for future travel needs and charging prices and another one is the exclusion of behavioural aspects such as range anxiety. Flath et al. (2013) suggest a heuristic approach as an extension of the linear program in order to take into account limited information for trips and prices.

[59] The fairness metric here is capturing the standard deviation of the utilities perceived by the EV owners, penalising those vehicles that charge at the expense of others.

In Galus and Andersson (2008), it is assumed that drivers aim to have at least 10% more energy than the amount used for their last trip. The benefit function with which they evaluate SOC has a linear part and a non-linear part that expresses satiation. If their marginal benefit is higher than the real-time electricity price then they are willing to charge their vehicle. Otherwise, they might not try to acquire energy. This is captured by their so-called "incentive rationality constraint"[60]. Their optimisation is formulated based on the mechanism design (MD) theory (Fudenberg and Tirole, 1991). A second constraint ("incentive compatibility constraint") aims to avoid strategic behaviour from customers that misleadingly report a value for the SOC, which is not true for them.

Table C.1 in Appendix C summarises all the papers mentioned in this chapter as well as in Chapter 2 that study the charging operation of electric vehicles. For those that apply charging coordination techniques, the scope and the optimisation methods adopted are presented. Moreover, some of the basic modelling parameters (or existing conditions for EV trials) like the vehicle mix or the available charging infrastructure are compared. Last but not least, this table shows the representation of driving and charging behaviour, which for most of the studies is based on exogenous statistical inputs or basic assumptions (e.g. according to time-of-day or peak-load periods).

The innovative elements of this dissertation as they are highlighted from this detailed review are:

- The main goal is to understand and explicitly capture out-of-home charging behaviour, whereas in most of the cases it is either neglected or considered as complementary to home-based charging events. Some previous researchers such as Hashimoto et al. (2013), Hutson et al. (2008), Saber and Venayagamoorthy (2009) and Su and Chow 2010 have also examined the charging coordination for parking facilities and most of them have analysed scenarios with V2G availability. However, they have not considered the customer preferences for charging and parking attributes that play a crucial role for the analysis under consideration.
- The endogeneity between charging control and the disaggregate response of EV drivers is captured with the discrete choice methods explained in Chapter 4. This endogeneity has been also taken into account by Daina (2014), but only in the context of home-

[60] In Chapter 6, instead of a constraint, this is applied to the choice-based framework through the alternative specific constant for choosing a charging alternative, vs choosing nothing.

based charging activities. Moreover, Knapen et al. (2011) have investigated the effects of EVs on the grid with an activity-based approach; yet, they have not combined the charging choices with a charging coordination method that would mitigate these effects. The same applies for Zoepf et al. 2013 that went a step further and estimated a mixed logit to capture drivers' heterogeneity with respect to recharge-timing choices. Finally, Waraich et al. (2013) have integrated a centralised smart charging algorithm in their activity-based micro-simulation, but the sensitivity of drivers to price variations was limited.

- It is the second attempt to express charging coordination as a revenue management problem for the aggregator/CSP. Nevertheless, the first one (Flath et al., 2012) is based on a single-resource approach while the representation of charging demand is relatively simplistic compared to the choice-based network RM formulation that will be presented in the next chapter.

5.3 Revenue management

5.3.1 Introduction to revenue management

Revenue management, also known as yield management, is a widely implemented technique in the service industry, most suitable for the provision of perishable goods or non-storable services. In other words, it is the creation and application of a suitable service to sell the right product to the right customer at the right price and time. The general attributes of companies that fit the criteria for revenue management applications are the following (Talluri and van Ryzin, 2004a):

- The company operates with a *fixed capacity*. When this capacity is reached, no more requests can be accepted.
- Consumers can be segmented into *distinct groups* with respect to their willingness to pay and their elasticity to price changes.
- When *the stock is not utilised in its full capacity*, there are economic losses for the company
- The product or the service can be *sold or reserved in advance*.
- There is an *observable fluctuation of the demand* on a daily basis and among different days as well.
- The *low marginal income from adding some extra capacity* makes this option economically non-profitable.

Firms that implement RM methods have to take decisions at two different levels: at a strategic level (initial allocation of capacity and long-term management of demand) and at a tactical level (short-term quantity and pricing decisions) (Talluri and van Ryzin, 2004a).

Revenue management was originally introduced in the airline industry after its deregulation in the 1970s. Seats in the same cabin were differentiated and operators started analysing thousands of requests per day to decide whether they should sell the seat in a discount fare or wait for higher-price sells in the future (van Ryzin and McGill, 2000). The significance of this technique was demonstrated by Delta Airlines that estimated $50 million annual revenue for the company by selling only one ticket per flight at its full price instead of accepting the reservation in the discount rate (Cross, 1997). Since then, there has been great progress in the field and comprehensive overview of the research undertaken can be found in Wen-Chyuan et al. (2007).

Two important steps in implementing RM are: the creation of a fare structure and the assignment of fare bases into a smaller number of distinctive booking classes[61]. Then inventory should be optimally allocated to these classes. When a firm uses capacity allocation decisions, i.e. accepting or rejecting reservations for various segments of customers in order to manage demand in an optimal way, revenue management is characterised as *quantity-based RM*.

The most conventional approaches to solving quantity-based RM problems for airlines are *booking-limit control* and *bid-price policy* (Bertsimas and de Boer, 2005; Talluri and van Ryzin 2004a). The former is based on the division of users in booking classes and on defining the optimal number of seats allocated to each group. If booking limits are *partitioned* then each booking class closes when all the respective seats are allocated. On the other hand, if booking limits are *nested* then the available capacity can overlap in a hierarchical manner. In other words, if the booking limit for class 1 (e.g. business travellers with higher willingness to pay) is 50 seats and the booking limit for class 2 (e.g. leisure travellers with lower willingness to pay) is 20 seats the effective capacity for class 1 is 70, allowing the unsold seats from class 2 to be allocated to users of the higher class.

[61] Fare base is the combination of the tariff that is assigned to the product and the conditions that come with this product (e.g. cancellation policies, advance purchase etc.). Booking classes are groups of customers that are assigned with the same fare class.

Bid-price policy suggests that requests for seats should be rejected until the ticket price has overcome the opportunity cost (also known as the bid price) of not being able to sell these seats later in the reservation period.

Quantity-based RM or capacity allocation problems can be classified in the following directions (Bertsimas and Popescu, 2003):

- Single-leg vs Network models
- Static vs Dynamic control

In static models, the number of seats that is going to be allocated to each market segment or customer class is defined in advance, thus allowing the protection of seats for the late-coming customers with higher willingness to pay. On the other hand, in dynamic control, the operator can modify his decisions based on the current conditions and the estimated future arrivals.

The simplest quantity-based RM models are the so-called **static single-leg** formulations with Littlewood's (1972) two-class model being the earliest example. The term static is utilised to distinguish these models from dynamic ones that allow arbitrary arrival orders. In Littlewood's model, if θ is the fixed *protection level* for high-fare seats (or rooms, parking places etc.), then discounted seats can be sold to the second class as long as θ seats are available for the first class. If the demand for high-fare seats is a modelled as a continuous random variable X, then the optimal protection level θ^* is:

$$P(X > \theta^*) = r \tag{5.1}$$

where r is the ratio of the price for the second class to the price for the first class.

Belobaba (1987) extended Littlewood's rule to multiple fare classes and introduced the *Expected Marginal Seat Revenue (EMSR)* heuristic. In EMSR, a probability distribution is estimated for each class and then the average fare of this class is multiplied by the probability that there will be sufficient demand, resulting in the expected marginal revenue for each incremental seat. However, here lies the risk of distributing the seats in a way that only marginally contributes to revenue maximisation. Belobaba and Weatherford (1996) suggested an extended version of EMSR to include sell-ups. Demand in these models is typically represented by customers that arrive in increasing order of fare classes.

Other researchers suggested a stochastic **dynamic** programming approach to the **single-leg** problem, where the remaining capacity of the single resource is the state variable and the quantity of demand to accept is the control variable. This approach can be implemented to examine various practical issues like overbooking, cancellations or no-shows. McGill and van Ryzin (1999) provide a very comprehensive literature review in this research area. The general formulation of this optimisation problem is given by the following Bellman equation:

$$V_j(x) = \max_{0 \le u \le \{D_j, x\}} \{p_j\, u + V_{j-1}(x - u)\} \tag{5.2}$$

where $V_j(x)$ is the value function at stage j, or the expected revenue when the remaining capacity is x, D_j is the demand at stage j, u is the control variable i.e. the quantity of the demand to accept and p_j is the price at stage *j.* As a result $p_j u$ is the revenue from selling u and $V_{j-1}(x - u)$ is the revenue to go from the next period. The maximum value of the decision variable is equal to the remaining capacity when the latter is smaller than the demand at period *j.* Otherwise, it is equal to the demand. The boundary conditions of the problem are $V_0(x) = 0$ for any x and $V_j(0) = 0$ for any j.

Revenue management in the hospitality industry has some distinctive characteristics that do not apply for airlines but could provide valuable insights for parking operators. For example, there is a second level of decision-making, the *operational level* (Bitran and Mondschein, 1994). At this level, the manager before allocating a room has to take into account the probability that customers will show up without reservations (*walk-ins*). Customers that request multiple day stays can further complicate this decision. For example, if there is a high occupancy for the following days, it may be optimal for the manager to reject a low-fare customer who requests a 3-day accommodation, even if the room stays empty for one night.

5.3.2 Network capacity allocation

In the airline industry, single-resource (or single-leg) control has become ineffective in revenue maximisation with the increase of hub-and-spoke networks and the growing number of itineraries including interconnected flights. *Network capacity allocation* was developed to take into account customers that require bundles of different resources. Williamson (1992) was the first to employ simulation-based techniques in order to highlight the increase in revenue performance when using network-based instead of leg-based methods.

In theory, it is possible to adopt the stochastic dynamic programming approaches, mentioned earlier, for network problems (Gallego and vanRyzin, 1997). However, in practice, these models in network RM usually suffer from the *curse of dimensionality* (Zhang and Adelman, 2009). High-dimensional state-spaces increase the computational burden and as a result decomposition approaches and approximations based on mathematical programming (MP) are adopted. Although being effective, the major deficiencies of these approaches are that they are *deterministic, static* and *partitioned* whereas network control methods are characterised by their *stochastic*, *dynamic* and *nested* attributes (Bertsimas and de Boer, 2005).

For most MP models, the term *booking class* is used to denote the combination of origin, destination and fare class (referred to as *odf*). For example, Glover et al. (1982) suggested the following integer programming model with a linear programming relaxation:

$$\begin{aligned} &maximize \quad && \sum_{odf} f_{odf} x_{odf} \\ &subject\ to \quad && x_{odf} \leq E\left[D_{odf}\right] \ \forall\ odf, \\ & && \sum_{odf \in S_l} x_{odf} \leq C_l, l = 1, \dots., L, \\ & && x_{odf} \geq 0 \end{aligned} \tag{5.3}$$

where f_{odf}: the fare/price of odf

$E\left[D_{odf}\right]$: expected demand for class odf

x_{odf} : number of seats allocated to class odf (the decision variable)

C_l : seat capacity of leg l

L : total number of legs

S_l : set of booking classes that use leg l

The purpose of this optimisation problem is to maximise the revenue from the seats that are allocated to the different *odf* classes. The first constraint guarantees that the number of allocated seats for a specific class never exceeds the respective demand. Moreover, the total number of accepted reservations is constrained by the capacity of each leg of the network. Finally, the decision variable cannot be negative.

A typical mathematical programming approximation method used in this case is the Deterministic Linear Programming (DLP) model. In the DLP approach, the demand for each product is treated as a deterministic quantity and a linear program is solved to find the optimal mix of customers to accept subject to the capacity constraints for each leg of the network. The DLP formulation is the following (Talluri and van Ryzin, 2004a):

$$\begin{aligned} V_j^{DLP}(\boldsymbol{x}) &= \max \boldsymbol{p}^T \boldsymbol{y} \\ subject\ to &\quad \boldsymbol{Ay} \leq \boldsymbol{x} \end{aligned} \tag{5.4}$$

$$0 \leq \boldsymbol{y} \leq \boldsymbol{\mu}$$

where $\boldsymbol{\mu}$ is the vector of mean demands for the n products, $\boldsymbol{x}$ is the vector of the leg capacities, $\mathbf{y}$ is the vector of decision variables i.e. the partitioned allocations for the n products and $\boldsymbol{A}$ is the incidence matrix[62]. It can be proved that the DLP results in an upper bound of the optimal value function. Essentially, this formulation is the same with 5.3, considering only the mean demand and ignoring the stochastic dimension of the problem due to the uncertainty in forecasts.

Instead of using directly the primal solution to the DLP model, the dual prices (or shadow prices) are utilised to construct the optimal control policy. Typically the shadow prices, that represent the displacement costs for individual legs, are used to decompose the problem into multiple leg-based problems that are easier to solve.

Since MP models are usually deterministic approximations of the dynamic program, there have been some efforts in the literature to incorporate stochastic demand. In this direction, Talluri and van Ryzin (2004a) have proposed the Randomized Linear Programming (RLP) model.

If the optimal solution to Model (5.3) is ${x_{odf}}^*$ then the optimal policy will allocate up to $[{x_{odf}}^*]$ seats to class odf. Thus, this is a partitioned approach, and it does not take into account nesting that could lead to increased revenue. One of the most common models for nested booking-limit control applications in network cases is the Displacement Adjusted Virtual Nesting (DAVN) model (Smith and Penn, 1988). In DAVN, an optimal set of shadow prices from the capacity constraints of the optimisation problem is used to calculate the displacement adjusted leg revenues. Then booking classes of similar adjusted-revenue are clustered in *leg buckets* for each leg, and booking limits are calculated for each leg bucket. The authors use the term "virtual nesting" because the high dimensionality of the problem does not allow the storage of availability for each booking class; nevertheless, it is tractable to determine them from the leg-bucket availabilities.

Similarly, *bid-price* policies can be modified to approximate network-based methods. Simpson (1989) has suggested a model where an optimal set of shadow prices is used to calculate the net contributions of each booking class to network revenue. This model was further analysed by Williamson (1992). If this net contribution is positive for an incoming request, then it should be accepted. As it was mentioned in the previous subsection for the EMSR method,

[62] Its elements a_{ij} indicate if resource i is used by product j. If yes $a_{ij} = 1$, otherwise $a_{ij} = 0$.

here lies the problem of marginal contributions. As a solution, bid prices could be dynamically updated after each booking period.

Other network-based booking control methods include:

- *Prorating:* This is similar to DAVN. The network problem is decomposed again in multiple leg-based problems and the revenue of a multi-leg flight is allocated over its legs (Williamson, 1992, Smith and Penn, 1988).
- *Approximate Dynamic Programming (ADP):* This is a form of certainty equivalent control where Model (5.3) approximates the value of the stochastic dynamic program (Bertsimas and Popescu, 2003).

5.3.3 Choice-based revenue management

Customer preferences have been traditionally modelled in RM using the independent demand model assumption. Under this assumption, customers arrive sequentially and place a request for a certain product, irrespective to the capacity controls applied by the operator as well as to market conditions (Talluri and van Ryzin, 2004a). As a result, demand is not endogenous to choice and purchase-timing behaviour.

However, it can be argued that treating demand in this way limits our understanding of purchasing behaviour. Choices like buy-up, diversion, or buy-down[63] and their revenue implications cannot be captured. Talluri and van Ryzin (2004b) introduced the theoretical background for *choice-based revenue management.* They explicitly model demand using a general discrete choice model and their optimal policy for a single-leg problem is to open sets sequentially from a family of efficient choice sets. They estimate the choice parameters using Expectation-Maximisation (EM) algorithms to evaluate and maximise an expected log-likelihood function.

The EM method is commonly used in RM applications because of the unavailability of non-purchase data. Online booking data do not provide information for customers that entered the system and did not purchase a product, or preferred to purchase from a competing company. As a result, this volume of potential customers needs to be inferred, and it is difficult to achieve it with standard maximum likelihood procedures. EM allows the simultaneous estimation of

[63] Buy-up is when a low-fare class is closed and the customer buys a higher one, whereas buy-down is when a high-fare customer prefers to buy a lower one if it is available. Diversion, for the airline industry, is when a discount class is closed and the customer chooses another flight for the same itinerary. In the framework that is presented in Chapter 6, this diversion could be the choice of an alternative parking facility for the same charging outcome.

choice parameters and arrival rates, by using arbitrary initial estimates to determine the expected values of missing data.

Newman et al. (2012) propose an alternative estimation method for choice-based RM that is computationally faster than EM. This method uses marginal log-likelihood functions and has structural similarities with limited information maximum likelihood (LIML) estimators.

In a simulation study (Vulcano et al., 2010), it was indicated that the integration of RM with explicit choice models could generate revenue increases between 1.5% and 5.3%. They also highlighted the possible existence of *framing* or *reference* effects, i.e. the product set offered by the operator affects the customers' valuation for the various product attributes. Likewise, the number of product attributes that are transparent to the customers (e.g. for opaque products some attributes are hidden before payment) might affect the revenue outcome. Lee et al. (2012) investigate air travellers' behaviour towards opaque products and explain why particular flight destinations were excluded in the choice process.

During the past few years, researchers have developed several techniques and heuristics to deal with the so-called *choice-base network capacity allocation* problem. The most prevalent model in this area is the *choice-based deterministic linear program* (CDLP), which is the natural choice-based analogue of the DLP model. The objective of CDLP is to define the optimal set of products to offer at each step, subject to the remaining leg-based capacity and booking time. CDLP is a deterministic approximation to the original stochastic problem (Gallego et al., 2004; Liu and van Ryzin, 2008a); yet its solution is asymptotically optimal for the stochastic case as demand and supply scale up proportionally.

Zhang and Adelman (2009) present an approximate dynamic programming approach to the above choice-based problem. After the linear program is formulated, they make an affine functional approximation to the value function in order to obtain dynamic bid prices, and then they use them into a decomposition heuristic that breaks the network problem into several single-leg problems. Likewise, Kunnumkal and Topaloglu (2010) follow a decomposition approach, based on an auxiliary optimisation problem, and they suggest that their solution is a tighter upper bound on the optimal expected revenue compared to the existing methods in the area.

Despite the deterministic nature of CDLP, it is still hard to apply for increasing number of decision variables due to its computational burden. With regard to this fact, there is a widely adopted relaxation of CDLP: the segment-based deterministic concave program (SDCP)

(Talluri, 2011). The objective of SDCP is again to define the optimal set of products to offer at each step, but this time for each segment separately. Consequently, the union of these subsets should provide a solution that is similar to CDLP. However, the consideration sets are now much smaller and the relaxed formulation can be solved with standard concave-programming methods.

Any service industry that applies RM is confronted with the risk of cancellations. Explicitly modelling these cancellations can lead to revenue improvements. Iliescu et al. (2008) have developed a hazard-based approach to model cancellation behaviour for airline customers but without integrating customer choice with the control process. Sierag et al. (2015) were the first to incorporate cancellations and overbooking[64] decisions in a choice-based RM framework. No-shows probabilities are reflected within the cancellation probabilities at the last steps of the optimization horizon and cancellation rates follow an exponential distribution. Their results suggest that by ignoring cancellations, operators might have revenue losses up to 20%.

The structure of the RM literature is presented in Figure 5.6. For each level of this taxonomy, the initials of the associated methods are illustrated in brackets. Then, moving from left to right and from top to bottom, each method is classified based on the previous levels. The last three boxes contain the computational approaches for single-resource RM, network RM and choice-based RM. The SDCP approach that is adopted for the analysis in Chapter 6 can be characterised as: *Tactical, quantity-based, multiple resources, static approximation of the dynamic program, booking limits or bid-price for optimal policy and DCM for demand representation.*

5.3.4 Parking and electricity pricing

As it was described in Chapter 2, parking pricing can serve for a variety of purposes: parking and mobility management, cover of initial investment, revenue maximisation etc. Pricing, especially when it is demand responsive, tends to enhance the efficiency of parking facility use. It can take the following forms (FHWA, 2012):

- **Fixed-rate pricing**. The most frequently anticipated type of parking pricing. It is related with very small variations according to location and time-of-day. These prices

[64] Overbooking is the action of selling a product/service in excess of the available supply to anticipate cancellations or no-shows. The risk here is that if the realised demand exceeds capacity some customers will not be able to buy/use the service, and this might cause dissatisfaction to them and additional costs to the operators.

are usually set based on supply and demand; however, they can't follow the changes due to inflation and evolution of demand.

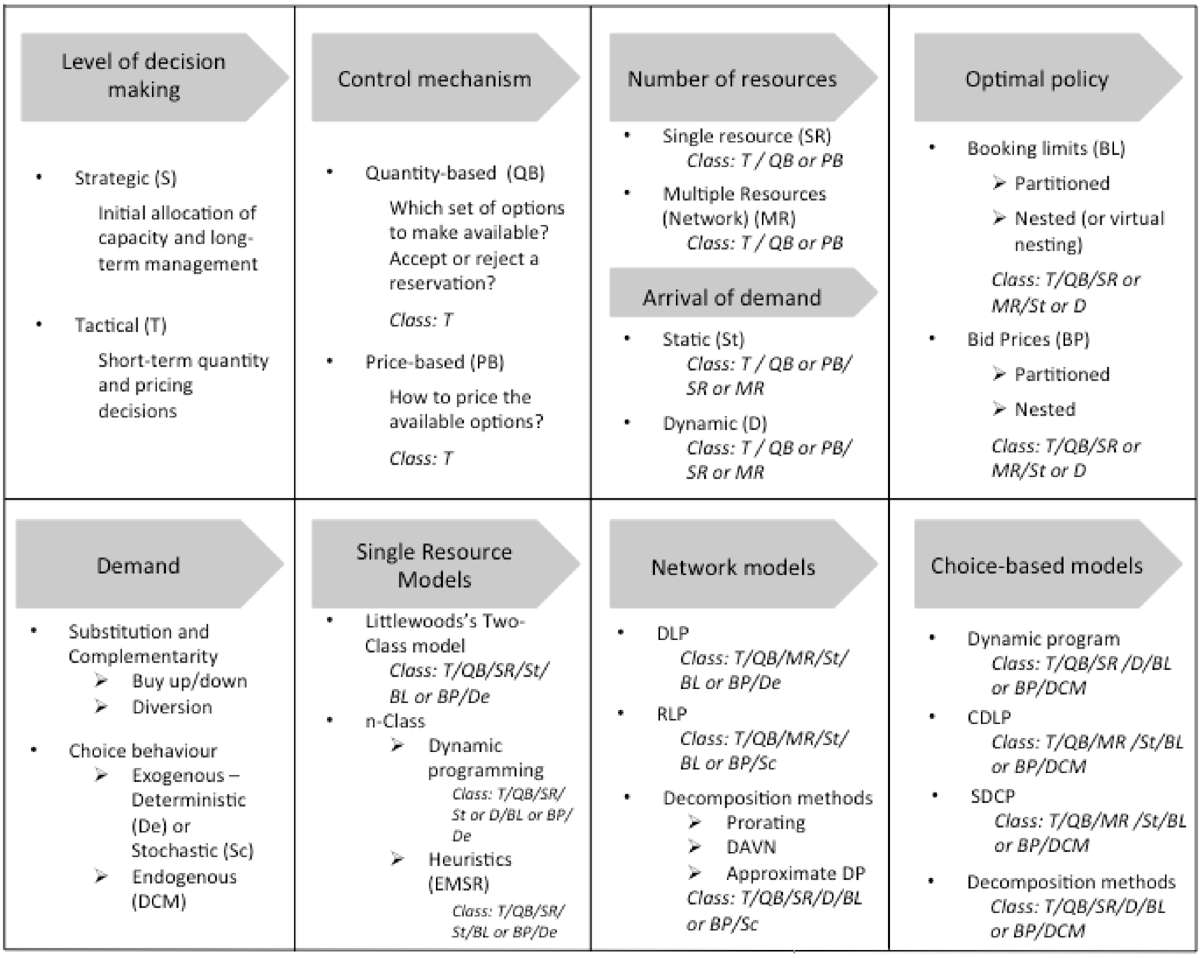

Figure 5.6: Classification of revenue management methods

- **Performance-based pricing**. Its purpose is to improve the performance of the system. Usually, for on-street parking, the goal is to maintain occupancy at a certain level below the full capacity in order to reduce parking search time.
- **Escalating pricing**. It is usually implemented in airport parking. Higher rates are charged for each incremental hour in order to ensure parking availability and turnover.
- **Dynamic pricing**. It allows the price to reflect real-time conditions; yet, it has been characterised ethically incorrect because consumers have not the full picture about future prices. In revenue management, when dynamic pricing is used as the technique to manage demand, it is called *price-based RM*.

Dynamic pricing is a financial instrument that can incentivize consumers either to reduce their consumption or to shift their consumption from peak to off-peak periods. In a smart grid environment, it can significantly reduce the uncertainties associated with electricity demand

(Roozbehani et al., 2010). Moreover, it can provide economic benefits both for consumers and utility suppliers (Faruqui et al., 2009; Samadi et al., 2010). If real-time prices are based on the power grid load, then dynamic pricing can also help in reducing peak loads (Oldequrtel et al., 2010). In a broader context, it can reduce the wholesale price of electricity and minimise investment costs for generation facilities and storage devices.

Electricity demand is characterised by temporal deviation, which cannot be captured with fixed-rate electricity prices. If this is not addressed, price is inelastic to demand and, as a result, the electricity market system is inefficient.

For out-of-home charging stations, it is anticipated that EV drivers will select to plug-in their vehicles only if the tariff is below an acceptable level. Charging prices could be hour-based or kWh-based, but it would appear that the majority of EV owners consider the latter to be fairer. In any case, local authorities should allow parking operators to decide themselves their charging strategy.

5.3.5 Dynamic pricing

The fast development of Internet and electronic businesses during the last decade has not only enabled but also stimulated the shift from static to dynamic pricing applications. The reduction of transaction costs that are associated with dynamic pricing as well as the fact that static prices can be inefficient in the volatile online environment are two of the main reasons for this paradigm shift (Narahari et al., 2005). Retailers, nowadays, have the opportunity to use automatic tools that compare their prices with their competitors' prices in real time, and hence, they can adjust them accordingly multiple times each day.

Perfect first-degree price discrimination would allow operators to extract the entire consumer surplus, resulting into an optimal pricing policy. Although this is impossible to achieve, for various reasons (e.g. competitive markets or difficulties in estimating WTP), the most powerful way to reach a near-optimal solution is to use data mining methods in order to collect past behavioural data and then to adjust prices accordingly. From the consumer's welfare perspective, personalised pricing might create a sense of unfairness due to a misunderstanding of price differences or overcharges to specific individuals.

Technological advances and specialised software development could give buyers the opportunity to monitor dynamic prices and make informed decisions. Miller (2014) comments: "Although consumers can protect themselves with anonymising technologies and price-comparison sites, it might be socially preferable to impose governmental regulation instead of a wasteful technological arms race. However, sweeping bans on the collection of consumer information would be unwise and overly restrictive of the free market".

Dynamic (or flexible or customised) pricing can be decomposed in two dimensions: a) dispersion in time and space and b) discrimination between different types of customers. In the revenue management area, the latter is achieved with the differentiation of the products based on the targeted market segments.

A comprehensive review of dynamic pricing methods can be found in Bitran and Caldentey (2003). Moreover, Narahari et al. (2005) classify the mathematical models that have been employed for dynamic pricing problems in the following categories: Inventory-based, Data-driven, Game theoretical, Machine learning based, Simulation-based. They also emphasise that there are several cases where combinations of the above categories are applied (e.g. data-driven machine learning models).

The optimisation models that have been presented for the choice-based network RM problem belong to the inventory-based category and so does the suggested methodology in this thesis. Also, the conceptual framework for a game-theoretical approach when the customers demonstrate strategic behaviour is presented in Chapter 6.

As it is stated in Zhang and Lu (2013), "Dynamic pricing for a network of resources is an important problem but is notoriously difficult to solve". In general, most of the RM applications are based either on dynamic allocation or static pricing methods without periodical changes of product prices. Some of the reasons that these approaches are preferred over full-scale dynamic pricing are:

- Firms do not always have full pricing flexibility
- There are customer acceptance concerns when there are large price variations for the same product among different customers
- Regardless the numerous years of research in the area, dynamic pricing problems with multiple products and multiple resources present difficulties in computation and implementation.

In the RM literature, the multi-product dynamic pricing problem was introduced by Gallego and van Ryzin (1997). Maglaras and Meissner (2006) have shown that this can be decomposed in multiple instances of a single-product pricing problem. The main assumption in these studies is that the firm operates either monopolistically or in a context of imperfect competition, so that if the operator varies the menu of prices, the demand for the respective products is affected. Furthermore, both studies present formulations for a network of resources (network RM problem) and a fluid representation of demand.

Only a limited number of studies consider dynamic pricing as an approach for network RM problems. Erdelyi and Topaloglu (2011) have implemented function approximations and proved that the upper bound to the expected value is tighter than with the typical deterministic linear programming formulation. Zhang and Lu (2013) have developed a resource decomposition approach, and after they have solved the single-resource problems they implement approximate dynamic pricing policies. Contrary to the deterministic approximation for the choice-based network RM problem that leads to an LP formulation, the deterministic approximation for "network" dynamic pricing leads to a non-linear constrained problem, which they solve with augmented Lagrangian techniques. Under the assumption that demand is modelled with MNL and disjoint consideration sets, the underlying deterministic approximation is a convex problem and hence has a feasible solution.

The authors have demonstrated that dynamic pricing can produce up to 6% revenue increase compared to static pricing solutions. They have also showed that static pricing performs better than choice-based dynamic allocation methods when prices are properly selected in advance.

In the domain of electricity use, Subramanian et al. (2013) present a dynamic pricing algorithm for day-ahead prices where customer choices are explicitly modelled with MNL. They solve the underlying Profit Maximisation Model (PMM) with the use of the reformulation-linearization technique (RLT), thus eliminating the non-linearity of the MNL term. In this way, their problem can be transformed to a mixed integer formulation, which is computationally tractable. Their MNL model is calibrated based on historical hourly electricity use data, including information from a previous dynamic pricing experiment.

5.3.6 Revenue management for the parking industry

Revenue management may have originated in the airline industry, but today it is applied in several industries that are bound by capacity constraints like hotels, car rentals and parking (McGill and van Ryzin, 1999). Electricity utilities have also introduced dynamic pricing systems for their end-users, but revenue management in the form of capacity control has not been observed yet in this area (Talluri and van Ryzin, 2004a).

The criteria for revenue management mentioned in subsection 5.3.1 do not only fit the case of parking reservation and management systems, but they also reflect the attributes of electricity as a commodity. As a result, for parking facilities with charging post availability, where parking services and energy for EVs are provided at the same time[65], RM is a fairly suitable method to implement.

Revenue management has already been adopted for car parking systems. Guadix et al. (2010) distinguish the procedure into four stages:

- Use historical data of service usage to forecast the demand.
- Develop an optimal space distribution model.
- Choose a method of controlling the parking space inventory (e.g. first-come-first-served, priority to distinct groups, nested provision of service etc.)
- Calculate the levels of real usage

The objective function for the optimal space distribution model consists of two parts: the individual reservations (standard, residential and commercial) and the reservations for groups of subscribers (daily pass, weekly pass and monthly pass). The operating hours are classified in peak and standard slots, and customer-specific prices are defined for each of them. Moreover, two different scenarios are evaluated: one with deterministic demand and one with stochastic demand where the number of parking arrivals might be greater than the predicted one. For the third stage of the RM procedure, parking arrivals are simulated with a non-homogeneous Poisson process. Also, three algorithms for the allocation of arrivals are investigated: first-come-first-served, distinct and nested.

In a similar direction, Akhavan-Tabatabaei et al. (2014) tried to establish the optimal number of subscriptions to accept (in a trade-off with drive-in customers) in order to maximise the overall revenue. Their RM approach is a hybrid mixture of optimisation and discrete-event simulation for a parking lot in the city of Bogotá, and it aims to maintain a standard minimum level of customer satisfaction. Users are statistically clustered into the two segments, based on historical parking data. Optimisation is achieved with a deterministic integer-programming model. Some basic performance metrics that are assessed after their simulation are: expected revenue, acceptance rate of drive-in customers, waiting time for subscribed customers etc. Furthermore, similar to an assumption for this thesis, an on-site operator is allowed to move the vehicles and allocate them more efficiently.

Parking RM should be accompanied by parking reservation systems (either Internet-based or smartphone applications) that advise drivers pre-trip and en route. There are many existing

[65] Electricity here works as a resale because the operator needs first to buy it from the electricity supplier

examples of parking reservation systems, especially for airports, but also for private facilities. After reservation, these systems could be implemented for internal facility guidance, i.e. leading drivers to available parking places. As with other reservation-based services, cancellations and non-appearance events are likely in the parking industry. Furthermore, a certain degree of flexibility is required so that there is remaining capacity for drive-in customers.

Teodorović and Lučić (2006) suggest an intelligent parking system that is based on fuzzy logic, has the ability to adapt and learn, and makes real-time decisions for the acceptance of parking reservations in a way that revenue is maximised. They assume that there are *m* tariff classes and members of each class pay a different hourly rate. Also, it is assumed that statistical information for arrival and departure times for these classes is available. The authors indicate that even though the objective of their specification is to maximise revenue, it can indirectly affect the traffic patterns and facilitate the spreading of traffic flows evenly in time. For example, if a low-fare class member is rejected a parking space, and he is not willing to pay the higher fare, he will probably have to alter his schedule (e.g. change activity time or mode of travel).

The SFpark program in San Francisco might not be a revenue management application since the main objective is to optimise performance and not revenue; however, it is probably the most successful implementation of dynamic pricing for on-street parking. As it is stated in Pierce et al. (2015), "A city should try to optimise the use of public garages, rather than to maximise revenue". Prices vary both by time and by location so that a certain level of occupancy is maintained. The occupancy rate that allows the most efficient operation of a parking garage in terms of parking search is between 85% and 95% and the price that has to be applied in order to maintain these rates, generates approximately half of the optimal revenue.

The first practical implementation of parking RM on a structural basis has been observed for the U.S. off-airport parking company, Park N' Fly (van den Eijnden, 2009). Market segmentation is easier to achieve for these services because they are based on the well-defined classes of air travellers (i.e. business and leisure users). Customers that made reservations were rewarded with discounted prices, compared to drive-ups. Time-series and statistical methods were adopted to predict customer arrivals and their length-of-stay. Finally, capacity control was based on the EMSR heuristic for single-resource models. RM resulted in 8% revenue increase and up to 70% increase of parking occupancy.

The complicated parking rates for various schemes (hourly rates, off-peak discounts, early-bird reservations etc.) along with the fact that the bill for some customers might include multiple rates (e.g. two peak hours and two off-peak hours) increases the difficulty both for parkers to process the price signals and for analysts to measure price responsiveness. For this reason, in the next chapter, a "package" of joint parking and charging options is defined in order to make more transparent the alternatives that are available for the drivers.

Flath et al. (2012) investigated a revenue management approach for the coordination of EV charging with respect to preventing bottlenecks in the local distribution level and in a larger scale (balancing of electricity demand and supply). The total amount of energy that can be provided to the users is a function of the transformer's power capacity and the charging duration of the vehicle. The energy providers offer distinct tariffs for EV users and the main difference with typical RM problems is that capacity is distributed in continuous and no discrete units (e.g. airplane seats, parking places etc.). It is also different in that charging can take place very often and in low cost, compared to other services where transactions are few and expensive. Vehicle owners are divided into two classes: those who have a regular charging demand (e.g. they charge their car while they are at work) and those with a short-term charging demand (e.g. a spontaneous reservation to park and plug-in the vehicle while shopping in the supermarket). At the end, the authors state their opinion that the benefits of RM are profound for future EV-related business models.

Parking lots can also be appealing for the implementation of V2G and the participation of EVs in electricity markets. Hashimoto et al. (2013) present an auction-based reservation system with V2G services included, demonstrating the potential revenue improvements for operators and comparing various parking management schemes. They assume that customers are billed for each hour they are parked, and they reward those with higher willingness to pay. Their assumption for discrete hour intervals for parking reservations (i.e. 10:00 am – 11:00 am instead of 10:20 am – 11:45 am) is similar to the approach adopted in this thesis. Fluctuations in demand are modelled according to actual parking data while willingness to pay is drawn from a probability distribution that is based on a questionnaire addressed to the parking users. Finally, the amount of discharging through V2G is randomly selected from a range that would not interfere with the drivers' travel needs.

5.4 Summary

The electricity system in the UK, as in many other countries, requires several financial and physical transactions among different agents. These transactions can be based on bilateral mutual agreements or emerge from real-time competitive market environments. In any case, electricity cannot be easily stored and there should be a reliable balancing mechanism between generation and consumption quantities. In order to apply such a mechanism, it is crucial to make robust predictions for future energy use on a disaggregate level. The additional recharging load from electric vehicles will complicate these predictions, due to its highly dynamic nature.

The choice modelling framework presented in Chapter 4 can capture the implicit preferences of individual drivers for charging characteristics, and hence it is ideal for forecasting energy use, assuming that these preferences will not significantly change for future drivers. Moreover, compared to standard exogenous assumptions for charging behaviour, which are usually encountered in the literature, this approach corrects for the endogeneity between the price of electricity and charging choices. How can CSPs take advantage of this knowledge and integrate individual decision making with their management strategies?

Charging coordination (or smart charging) techniques for EVs have been given tremendous attention during the last few years, with hundreds of studies investigating control methods, looking at the problem from different perspectives. The diverse impacts that clusters of plugged-in vehicles can have on the power system, as well as various optimisation methods that have been applied to mitigate these effects, were listed through a detailed review in the present chapter. Most importantly, the added value of this dissertation in terms of modelling the drivers' response to these control methods is highlighted.

However, what tends to be neglected is that new business models are required so that parking operators are motivated to install and operate charging infrastructure. It's highly likely that charging coordination will be assigned to CSPs, who in turn will have to maximise the revenue for the parking operators. The limited power capacity and the increased uncertainty for out-of-home charging demand are two of the main reasons that this maximisation has been formulated as a revenue management problem.

In the next chapter, an airline-RM heuristic is demonstrated and transformed for the optimal allocation of charging posts to EV drivers that make reservations in advance. The benefits from modelling demand with the discrete choice specifications developed earlier in the thesis are illustrated through a case study for London.

6 CHOICE-BASED REVENUE MANAGEMENT FOR CHARGING SERVICE PROVIDERS

6.1 Overview

As it was explained in Chapter 5, smart charging requires an EV supplier-aggregator (EVSA) or a charging service provider (CSP). This intermediate unit will manage the timing of individual charging events with respect to the optimisation of one (or a combination) of the following: power losses, costs for power network stakeholders (operators, suppliers, generating units etc.), costs for individual drivers, integration with renewable sources and balancing of demand and supply.

Considering out-of-home charging infrastructure, the role of the CSP is to guarantee a certain SOC for the EV drivers by the time they want to leave the charging facility, and at the same time coordinate charging operations in a way that grid constraints are satisfied and revenue for the associated parking operators is maximised. In other words, they have to provide services in three directions: individual **EV drivers**, **power system operators** and **parking operators**.

Parking operators will have the opportunity to act as Charging Point Managers (CPMs), and despite being end users of electricity they will be able to make an agreement to resell it to third parties. As a result, charging operation in privately owned facilities should be a responsibility for CPMs or EVSAs.

The direct and indirect roles of the CSP can be summarised in Figure 6.1. In general, they can be classified in *strategic* (e.g. indirectly affect planners and manufacturers for the initial allocation of charging infrastructure) or *tactical* (e.g. satisfy the energy needs of the drivers). The three directions mentioned earlier belong in the tactical area or the dynamic operation area, which needs to be continuously updated by the CSP according to charging demand predictions.

This chapter provides insights both for the dynamic operation area, as well as for the initial capacity allocation, through a set of sensitivity analyses.

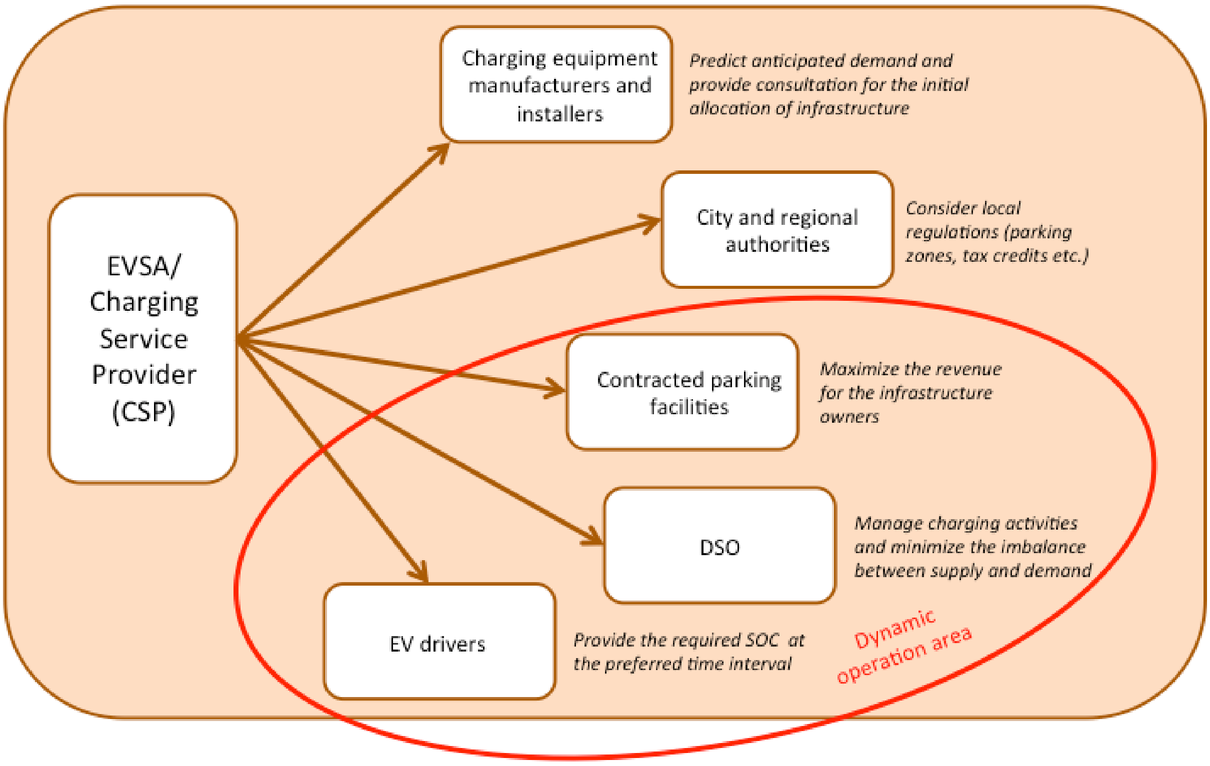

Figure 6.1: CSP roles and interactions with third parties

Existing smart charging applications, typically take advantage of EV fleet load flexibility. Load flexibility is translated as the degree of freedom that the CSP has in controlling charging operation as long as the requirements of individual EV requests are satisfied. On the other hand, inflexible loads apply when the CSP is constrained by the client in the choice of supply periods. Ideally, charging events with low average power rates should be incentivized with the appropriate price signals (Bessa and Matos, 2013).

The revenue management specification that is presented in this chapter, as a solution to the charging coordination problem, is differentiated from the above applications in the treatment of load flexibility. From one perspective, EV drivers have full control of the charging process since they select a pre-defined package of charging rate, time and location. Consequently, there is no uncertainty in the time that their requested SOC will be delivered. On the other hand, the inflexibility of this approach is not limiting for the CSP because the management and allocation of resources are optimised in advance and not in real-time. Therefore, the uncertainty associated with the arriving demand is minimised and the incentives for low power rates are achieved with the appropriate pricing of the respective "packages" or "charging bundles".

The modelling framework that is presented in this thesis allows a closed-loop integration of this decentralised control method with the charging preferences of EV drivers as well as the quantification of the impact that the supply side has on the demand side and vice versa.

The estimated parameters from the stated preference exercise of Chapter 3 are implemented in SOCSim (Services for Optimal Charging Simulator), a micro-simulation framework that has been developed, where activity patterns are synthesised from a London-based travel diary. Different penetration rates of electric vehicles are evaluated for two characteristic areas: one where shopping activities are dominant and one where working activities are dominant. The combined charging/parking and activity timing choices for the simulated vehicles possibly produce modified daily schedules, and charging requirements for the associated trips affect the set of charging bundles that are offered by the CSP.

SOCSim is used afterwards to compare the uncontrolled scenario with the revenue management model and the added value of the latter is assessed through a set of sensitivity analyses. As a result, this chapter combines the presentation of the modelling framework with an empirical application and recommendations to a CSP for its practical implementation.

In particular:

- Section 6.2 presents the conceptual framework of the revenue management model
- Section 6.3 explains the steps followed to create the simulation tool for the empirical application
- Section 6.4 demonstrates an uncontrolled scenario that is based on first-come-first-served accommodation of the EV charging demand
- Section 6.5 presents an offline choice-based optimisation of the pricing schedule for the CSP
- Section 6.6 adopts the optimal prices from section 6.5 for the development of the choice-based network revenue management model
- Section 6.7 describes the theoretical basis for extending the conceptual framework to take into account strategic behaviour of EV drivers
- Section 6.8 recommends the necessary steps to turn this framework into a real-world application
- Section 6.9 summarises and presents the main conclusions

6.2 Conceptual Framework

6.2.1 Two-step optimisation

The conceptual framework of the revenue management that is developed in this thesis is presented in Figure 6.2. After accumulating the required inputs, the CSP first designs the range of charging bundles that are going to be offered to the customer segments. The class-specific charging preferences of these segments are estimated with the latent class model that was presented in Chapter 4.

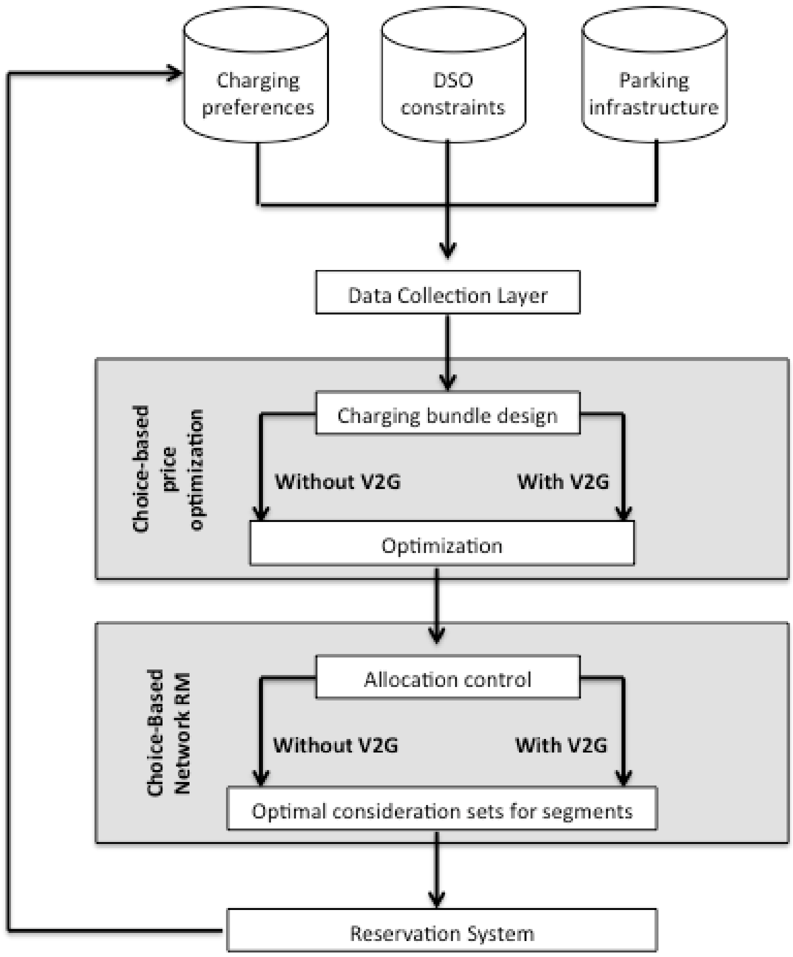

Figure 6.2: Conceptual framework of revenue management for Charging Service Provider

The offer set can vary according to the decision of the operator to provide V2G services or not through the contracted parking facilities. After defining the charging bundles (i.e. combinations of charging rate, location and time-of-day), the CSP can apply an offline optimisation that receives as inputs the exogenous demand and the sensitivities to charging characteristics and creates as output a vector with the optimal price for each charging bundle, consistent with the applied scenario.

Nevertheless, this approach does not take into account the dynamic nature of demand and the potential revenue losses from not controlling charging requests in real-time. In the literature, dynamic optimisation problems for network RM are typically solved with quantity-based methods, i.e. dynamic capacity allocation[66]. For improved results, the optimised prices from the previous step are used as input, while now the decision variables are the optimal offer sets that should be provided to different market segments for each step of the reservation period.

As a result, the suggested framework is based on a *reservation system*, where customers have the opportunity to book a charging post 24 hours in advance of their preferred arrival time at the parking lot. The availability of charging places with their respective prices and other characteristics have to be displayed online by the CSP, in order for the system to be applicable.

6.2.2 Multi-dimensional capacity

The model developed in this chapter receives as input the spatiotemporal preferences of EV drivers for out-of-home charging and optimises the control process for a CSP. This optimisation is based on two capacity dimensions: the availability of *charging posts* in the contracted parking facilities and the *power capacity* provided by the local DNO. The motivation behind this approach is to design a service that will maximise revenue for the CSP (and respectively for the charging-equipped parking facilities) but at the same time, it will optimally distribute the incoming charging demand, in order to avoid peak loads and bottlenecks at the power distribution level.

In the majority of revenue management problems, the capacity of the perishable product has a single dimension (e.g. airline seats, hotel rooms etc.). Nevertheless, there are services that present *multiple capacity* attributes, such as the case of container liners, where shipping capacity is measured both in volume and in weight (Xiao and Yang, 2010). Likewise, in the operation of EV out-of-home recharging, there is a certain power capacity (which is variable throughout the day) that the CSP can provide to the customers as well as a fixed number of plug-in places for each parking lot. Schematically, if charging services are provided for two parking facilities, the two capacity dimensions are represented in Figure 6.3.

In this figure, P denotes the power in kW and P_{EV} is the available power for recharging, after taking into consideration the required power for non-charging activities in the area, depicted by the shaded area above P_{EV}. The CSP might benefit from allocating more of the P_{EV} capacity to the busiest parking lot. Customers can choose to charge with different rates and for varying

[66] The difficulties in the application of network dynamic pricing methods were explained in subsection 5.3.5

charging intervals, based on their desired SOC at the end of the parking event and the power availability. Assuming that the charging duration of a customer i is CD and his preferred charging rate is $P_{EV,i}$, the total amount of energy conveyed to the vehicle's battery is $E_i = CD * P_{EV,i}$. While consuming electricity from the grid, EV drivers also occupy the provided charging posts, which can be disproportionally allocated among the parking facilities. For example, $EV_1$and EV_2occupy a charging post of the same facility at different times, as it can be seen in the right part of Figure 6.3. Nevertheless, EV_2 is using a higher recharging rate for a shorter period. The area of each rectangle at the left part of Figure 6.3 represents the total amount of energy (in kWh) that is consumed by the respective EV.

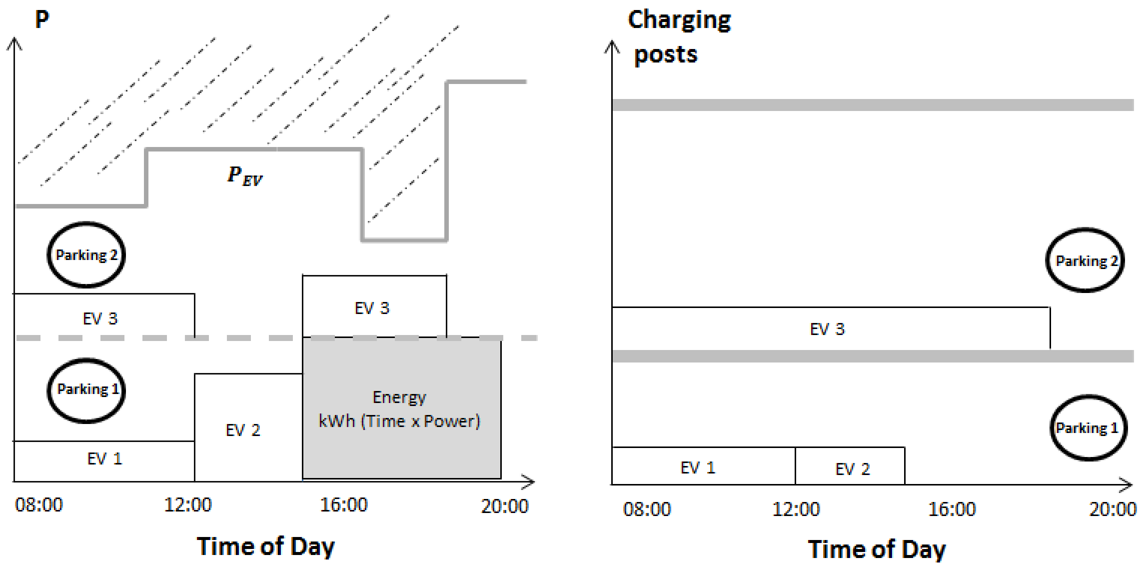

Figure 6.3: Available charging capacity P_{EV} and available charging posts in a typical day for two charging-equipped parking lots

Flath et al. (2012) have developed a similar approach to represent capacity in their RM-based charging allocation problem. However, their model is constrained by a single-dimension power capacity and they do not allow EV drivers to choose amongst different recharging rates or different charging durations.

6.3 Empirical application

6.3.1 Simulation setup

The charging coordination achieved with the developed revenue management system is demonstrated through simulation. The data comes from the London Travel Demand Survey[67] (LTDS) (TfL, 2011) and particularly the trips around:

- The Westfield shopping centre, one of the largest urban shopping malls in Europe and
- The Canary Wharf station, one of the busiest working areas in Central London

in order to represent out-of-home charging behaviour related to shopping and working activities for high-demand areas. The Westfield Shopping Centre in the White City district of London attracts a significant amount of shopping and leisure activities (63,000 visitors per day approximately for its first year of operation) (Bishop, 2009). On the other hand, the redevelopment of the Canary Wharf area, with the relocation of large banks and other financial institutions, led to a quadrupling of the number of workers during the last decade (from 27,000 to over 100,000) (Allen, 2013).

The electricity demand for these areas is increased compared to typical residential districts of London, especially during working hours (e.g. display lighting for retail shops or climate control and personal computers for office buildings). A common strategy is to use models of building energy consumption and simulated occupancy to estimate resource demands (Keirstad and Sivakumar, 2012). For this thesis, the daily distribution of electricity consumption for the local network (1 km^2 around the shopping centre and the Canary Wharf underground station respectively) is depicted with load profiles of domestic and non-domestic customers for a typical winter weekday[68].

Westfield is located in the London Borough of Hammersmith and Fulham where the average resident population density is 11,148 people per km^2. (ONS, 2014). Moreover, the shopping centre has a workforce of approximately 8,000 employees, mainly occupied in retail and catering (Westfield, 2012). Canary Wharf is located in the London Borough of Tower Hamlets, which has the second highest population density among the UK districts (14,201/km^2). In this local authority, domestic consumption makes up less than 20% of the total electricity

[67] LTDS is introduced in subsection 3.2.1.
[68] The load profiles represent the pattern of electricity usage by day for an average customer. The profiling data in this chapter is drawn from Elexon (operator of wholesale electricity market in the UK) and in particular, from Profile Class 1 (Domestic unrestricted customers) and Profile Class 3 (Non-domestic unrestricted customers) (https://www.elexon.co.uk/reference/technical-operations/profiling/)

consumption while the remainder is used by non-domestic customers (DECC, 2014b). If the load profiles are scaled up based on the resident and working population densities above, the resulting daily load curves would resemble those of Figure 6.4.

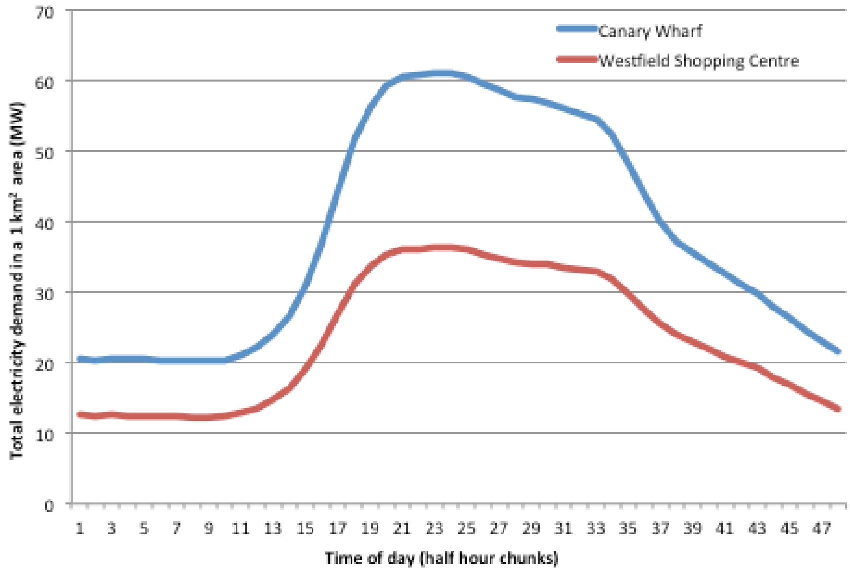

Figure 6.4: Aggregated demand profile for the examined areas, for a typical winter weekday

Typically, electricity demand is modelled after analysing the working cycles of specific appliances and combining this information with activity scheduling and occupancy levels for the building that is examined. Thereafter, various consumption profiles are generated and aggregate load curves are synthesised with the use of probabilistic methods. The difficulties in obtaining appliance-level data for the areas of interest as well as the sophisticated approaches that are required for energy consumption modelling were out of the scope of this thesis. As a result, the typical profiles were adopted from existing datasets and the population densities were used as an approximation to the probabilistic techniques.

Regarding the installed capacity, distribution transformers come in discrete sizes and are usually replaced when the available headroom (i.e. the difference between the installed capacity and peak electricity demand) reduces to zero. Therefore, the available headroom can vary greatly from one distribution network to another. For this reason, three scenarios are tested for the available headroom (0%, 10% and 20%) in order to take account of this spatial variability (these scenarios for the Canary Wharf network can be seen in Figure 6.5).

Based on the location of existing parking facilities in these areas, it was decided to investigate the effect of charging activities in a 1km^2 radius from the Westfield shopping centre and the

Canary Wharf underground station. The CSP is assumed to operate two parking[69] facilities ("Parking One" and "Parking Two") for each case. Using the LTDS dataset, the following screening procedure was applied:

- Only home-based car-driving daily tours were retained for the analysis.
- If these tours did not include an activity in one of the areas of interest they have been removed
- A twelve-hour span (09:00 am – 21:00 pm) was initially selected as the operation period for the parking facilities and activities extending out of this time-window were excluded from the analysis.
- For individuals that had multiple activities in the examined area, it was assumed that the charging event would take place at the destination with the largest parking dwelling time.
- Activities with small duration (less than half an hour) were not considered as potential charging opportunities for the drivers.
- The remaining sample includes 204 parking events for Westfield and 157 parking events for Canary Wharf.

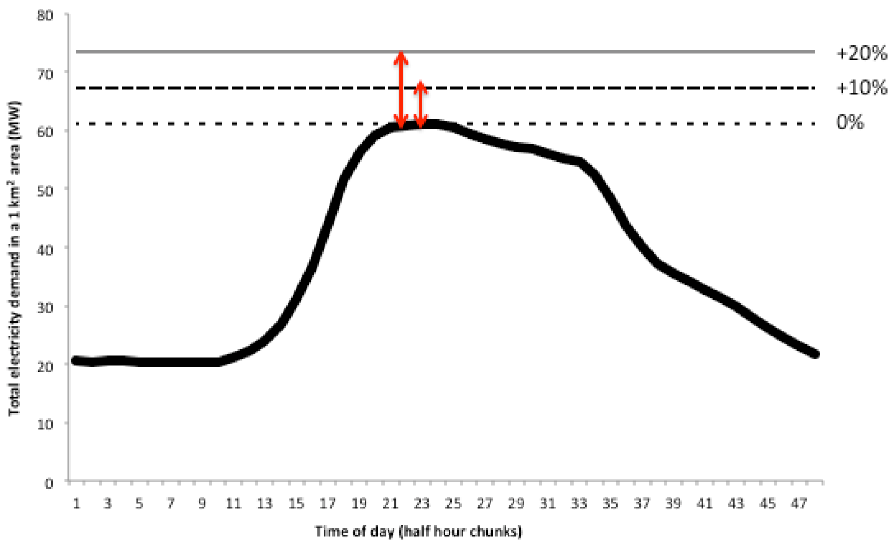

Figure 6.5: Installed capacity scenarios for the distribution network of Canary Wharf

For the remaining trips, the total daily driving mileage is calculated and then used to approximate the amount of energy in kWh that is required. Since out-of-home charging is more appealing for BEV drivers than for PHEV drivers, it was assumed that the portion of plug-in

[69] The model could be applied from a whole city down to a few car parks; however, the computational complexity is significantly growing with the scale of the simulation.

vehicles for each scenario consists only of BEVs. In particular, energy consumption is estimated according to the electric fuel economy of Nissan Leaf, which is one of the most competitive fully electric vehicles currently in the market. The electricity consumption of the Leaf (2013 model) is 29kWh/100 miles (combined city and highway driving) (EPA, 2013), which is translated into a range of 83 miles for its 24kWh battery capacity. The energy quantity requirements are calculated based on the total daily driving needs in order to reflect a lower home recharge potential and consequently, a higher need for out-of-home charging services. Finally, they are divided by the efficiency of the charging infrastructure (approximately 80%) to give the additional burden to the distribution power network.

6.3.2 Population synthesis

In order to investigate the effects of the charging demand on the power network and the revenue implications for the CSP, the trip sample needs to be scaled up, so that it is representative of the total demand for parking in the two areas. This is achieved by generating a synthetic population from the available individuals.

Population synthesis is commonly used for activity-based micro-simulation models, since calibration, validation and forecasting for such systems depend on household and person information (e.g. income, car ownership etc.) for the entire population of a specific region (Beckman et al., 1996). Typically, this disaggregate information is only available for a random sample and not for the whole population. On the other hand, marginal distributions for the attributes of interest can be obtained from Census data. The formulation of synthetic populations is based on the selection of households and persons from the random sample, in a way that the joint distribution of the aforementioned attributes matches the census-based marginal distributions.

The most widely adopted method to estimate the joint distribution among a set of control variables is the Iterative Proportional Fitting (IPF) algorithm (Ortuzar and Willumsen, 2011). To implement the IPF method, first, a frequency table is created where each cell is a multi-dimensional category expressing a unique value combination of the one-dimensional control variables. Then, the aggregate information that is available from the census data is used as a starting point for the IPF procedure, and the algorithm cycles iteratively through a group of control totals (one for each category of the employed control variables). At the end of this multi-proportional adjustment, the initial joint distribution is replicated and all control totals are satisfied. Zero cells in the trip sample were replaced with 0.01 in order to avoid creating zero entries in the synthetic population.

Once the joint distributions are estimated with the IPF method, they are used to randomly draw households (or persons) from the sample and generate the synthetic population. If the position of the person within the frequency table is C, then the selection probability for each person is given by:

$$P_p = \frac{M_C}{N_p} \frac{W_p}{\sum_{i=1}^{N_p} W_i} \tag{6.1}$$

where P_p is the selection probability for person p, M_C is the number of persons p in cell C of the frequency table, N_p is the total number of persons in the area of interest and W_p is the person weight. If the person is added to the synthetic population, M_C is reduced by one, and a person of that type is less likely to be selected in the future (Mohammadian et al., 2010).

In this study, the control variables that have been selected for the population synthesiser are the class membership parameters of the latent class model in Chapter 4. In particular, five categorical variables have been used:

- Age (3 categories): 20-39, 40-59, 60+
- Gender (2 categories): Male, Female
- Employment status (2 categories): Employed, Not employed
- Marital status (2 categories): Married, Not married
- Parental status (2 categories): Having children, Not having children

The marginal distributions for the entire population come from the Greater London census data (Census Information Scheme, 2011). The total number of persons entering the areas of interest was estimated proportionally to the ratio of the final sub-sample to the LTDS dataset. Moreover, the joint distributions of the personal characteristics were matched to the aggregate information for the whole Greater London. Ideally, boroughs where incoming trips had their origin (household locations) should have been examined separately, but the limited amount of individuals for each region was restrictive for this approach.

These simplifications and alterations of the conventional population synthesis methodology, as it was described earlier, should be associated with some caveats. For example, it is possible that the employment rate for those that undertake activities at Canary Wharf is not representative of the employment rate in Greater London. An alternative approach would be to scale up from the random sample to the population level using the appropriate person weights. Nevertheless, the main reason for generating synthetic individuals is that the charging coordination techniques presented later in this chapter are based on demand heterogeneity.

The errors associated with the technique described above could be mitigated by using the selection probability of equation 6.1 to draw multiple populations instead of one. However, there are several scenarios that are going to be investigated later in this chapter and evaluating these scenarios for different synthetic populations would be a cumbersome task.

As a final step, it is essential to generate the trip attributes for the synthetic population (e.g. travel distance and parking duration) and some additional personal characteristics that will be used as inputs for the choice-based control model (e.g. income band and day of the week that the daily tour takes place). This is achieved by the employment of a pseudo-random number generator that produces a series of random numbers that follow a specific parametric distribution[70]. First, more than 20 well-known parametric distributions are fitted to the LTDS sub-sample for each of the variables of interest. Then these distributions are compared with the probability density plot of the observed attribute in order to find which one describes better the actual observations. Finally, the pseudo random number generator creates a set of uniform random numbers that are substituted into the inverse of the selected cumulative distribution.

This procedure results into 14,467 parking events (i.e. activities) for Westfield and 10,921 parking events for Canary Wharf. Three scenarios for the level of BEV penetration in the market are evaluated: 25%, 50% and the extreme case where all the vehicles are BEVs[71]. For each of the scenarios, it is initially assumed that all drivers plug-in their vehicles and start charging as soon as they reach their activity destination. The charging event coincides with the parking event and consequently the charging rate is equal to the estimated energy quantity divided by the parking duration. This "dumb charging" strategy allows the estimation of the demand for electricity and hence it is essential for the strategic allocation of power capacity between the two parking facilities.

[70] Alternatively, the attributes of interest could have been drawn from the data. While the parametric distributions are independent, this approach would allow the joint distribution of the trip and personal characteristics.
[71] These scenarios are similar to those analysed by Schneider et al. (2008) but in their study the assumptions are made for PHEVs and not BEVs.

6.3.3 Daily distribution of charging demand

Figure 6.6 shows the distribution of energy requirements for the extreme scenario of 100% BEV penetration, which is estimated based on the individuals' daily travel distance. The curves for both areas are strongly skewed towards small quantities in order to capture the "top-up" character of out-of-home recharging.

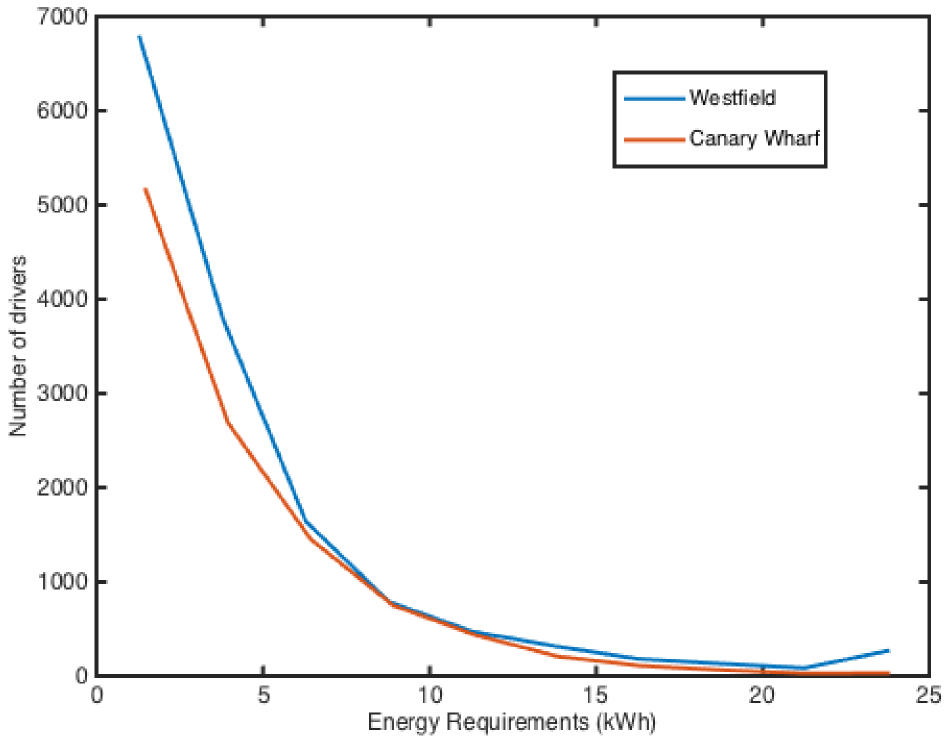

Figure 6.6: Distribution of energy requirements for the synthesised population

Figure 6.7 and Figure 6.8 demonstrate the additional demand from the recharging of electric vehicles if "dumb charging" is adopted. For this "dumb charging" scenario, the allocation of power demand is deterministic (i.e. vehicles start charging directly after plugging-in) and as a result, there is no uncertainty regarding the values presented in these figures. On the other hand, the First Come First Served algorithm that is applied later in this section draws from the logit probability for the charging choice, and hence, the outcome of the simulation is stochastic.

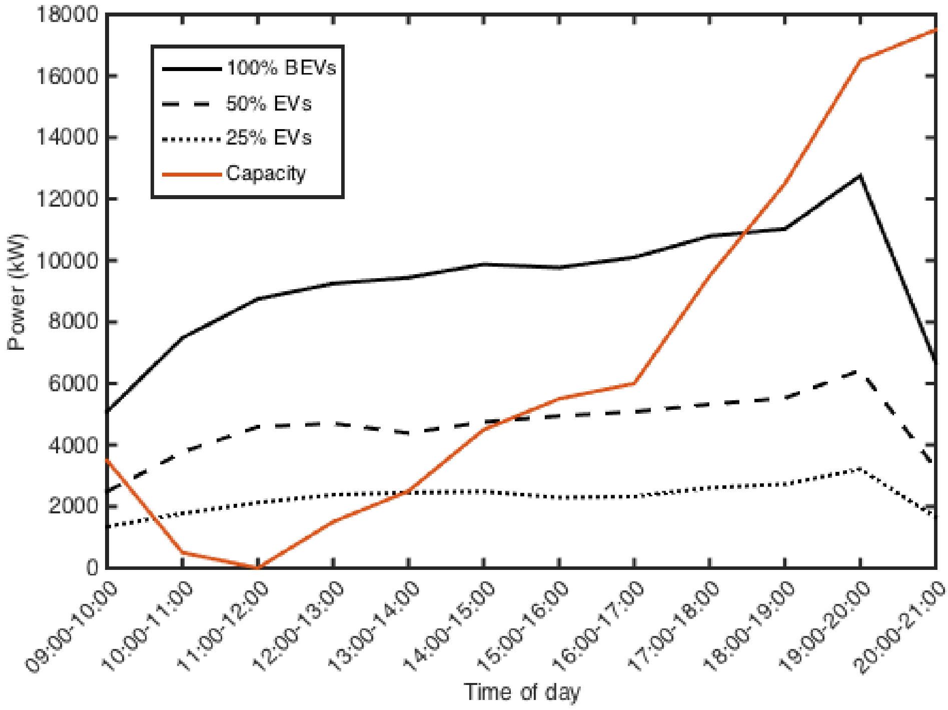

Figure 6.7: Power demand with “dumb charging” for the three scenarios and power capacity for Westfield area

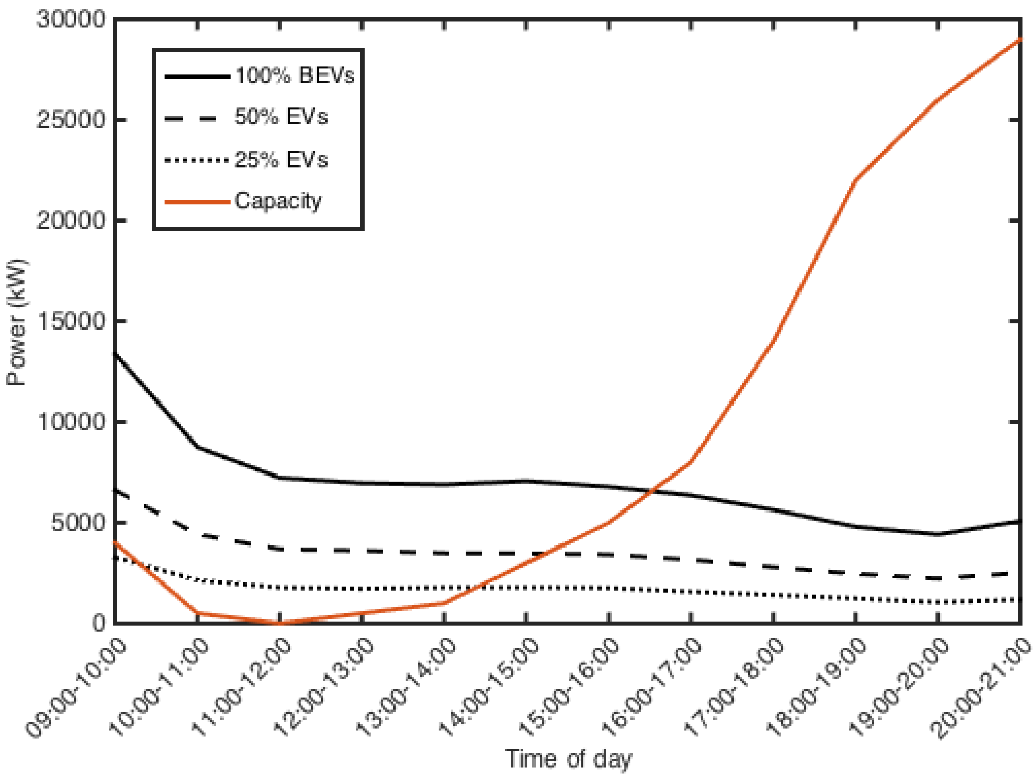

Figure 6.8: Power demand with “dumb charging” for the three scenarios and power capacity for Canary Wharf area

The three BEV penetration scenarios are compared with the power capacity when the available headroom for the local substation is zero, and hence, it's not possible to provide charging services to the drivers during peak electricity demand (i.e. between 11:00 am and 12:00 pm). It can be observed for both areas that as the proportion of BEVs is increasing, the time-window where capacity exceeds charging demand is decreasing. For example, if BEVs replace all conventional vehicles, the distribution power network can fully accommodate plugged-in vehicles only during the period 17:00 pm – 21:00 pm.

Evaluating alternative scenarios where the available headroom is greater than zero would shift the red curves of Figure 6.7 and Figure 6.8 upwards in discrete amounts (e.g. 10% or 20%). As a result, the amount of BEVs that cannot be accommodated under the assumption of "dumb charging" will decrease.

For the pre-allocation of power capacity, it is also assumed that drivers plug-in their vehicle to the parking facility that is closer to their final destination. Since it is assumed that Parking One is the nearest to the centroid of the designated area (both for Westfield and Canary Wharf), the charging demand for this facility is higher compared to Parking Two (Figure 6.9). Apart from strategizing the initial allocation of the available power for the optimisation problem, the spatial distribution of energy quantity allows the implementation of demand-side management methods that are driven by spatial parameters (i.e. locational pricing).

The CSP could also use this information in order to plan future installations of charging infrastructure. Predicting the demand for electricity is vital for the coordination of charging events as well as for the maximisation of revenue from the contracted parking facilities. In addition, when the CSP decides the proportion of the power capacity that should be reserved for EVs, he has to take into account the imbalance costs that could be incurred from the "unsold" power, especially during peak hours with increased wholesale electricity prices.

In the following section, the charging bundles that can be delivered by the CSP are defined and the individual preferences for the attributes of these bundles are presented, based on the estimates from Chapter 4. The choice model is applied in three different contexts: a) a first-come-first-served (FCFS) algorithm where there is no optimal control and the incoming charging requests are allocated sequentially, b) a pricing optimisation formulation where the best tariff structure for the provided bundles is defined, and finally, c) a network revenue management formulation with dynamic capacity allocation, which is continuously updated according to the realisation of demand throughout a reservation-based system.

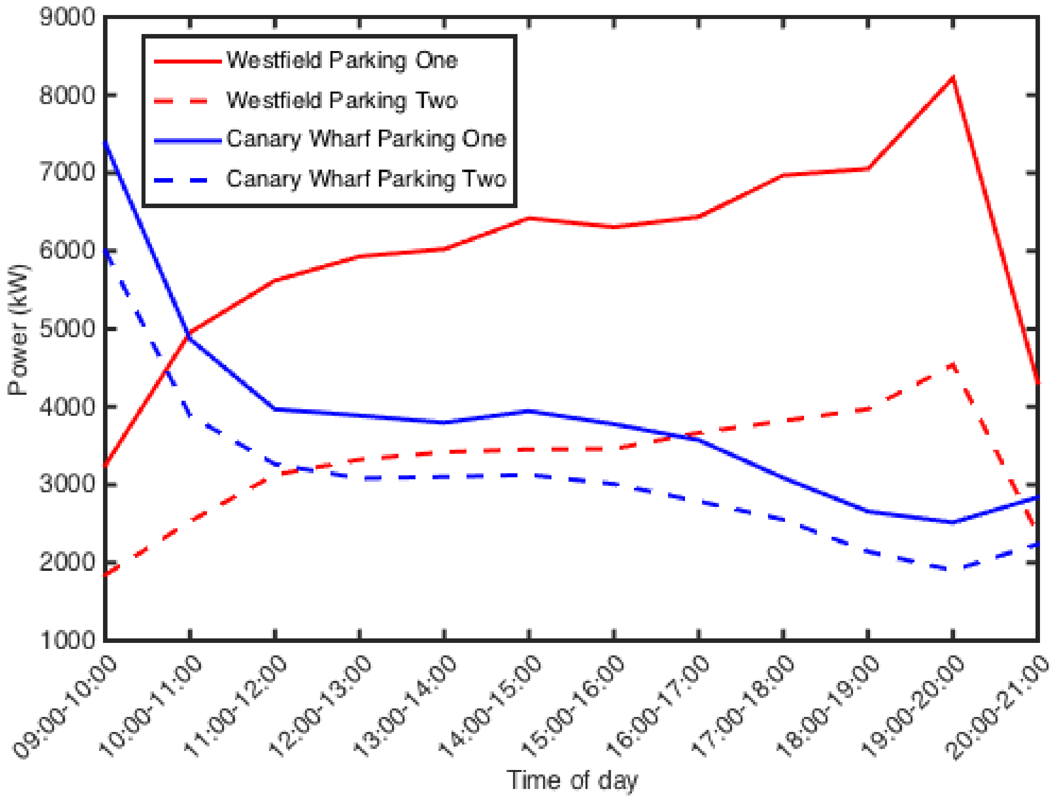

Figure 6.9: Differentiation of power demand between the two parking facilities at Westfield and Canary Wharf

Charging coordination is evaluated for a:

- Non-Locational Pricing (NLP) system, where there is no spatial differentiation of price among similar charging bundles and a
- Locational Pricing (LP) system, where drivers are incentivized to plug-in their vehicle at areas with reduced levels of electricity demand

The simulation framework (SOCSim) presented in this subsection could be summarised in Figure 6.10.

6.4 First-come-first-served Scheduling (FCFS)

The network revenue management specification developed later in this chapter is a highly dimensional problem that escalates exponentially in computational expenses for increasing hourly slots. For this reason, it has been decided to isolate the four-hour period with the highest limitations in power availability (09:00 am -13:00 pm). The synthesised charging events are discretised in sets of one-hour slots, i.e. 1,2,3 and 4-hour charging durations for the examined time-window. Subsequently, the CSP can design a certain amount of “charging bundles”, targeted to the various customer segments.

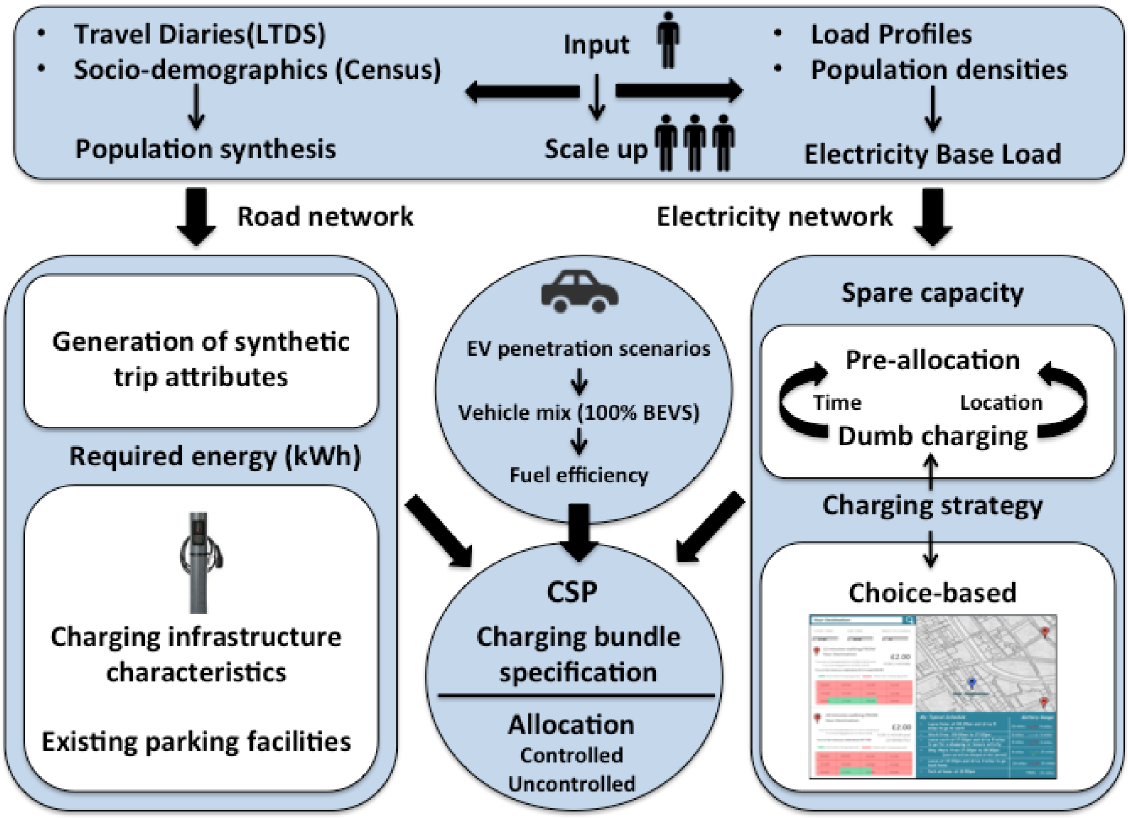

Figure 6.10: Framework for SOCSim micro-simulation

As it was highlighted in Chapter 3, rapid DC chargers are excluded from the analysis because they are not representative of typical urban charging infrastructure. Therefore, it is assumed that the CSP offers charging services with four discrete rates: A=3kW, B=6kW, C=8kW and D=12kW.

In order to tailor the CSP services to the users, a three-level segmentation was followed. First users were segmented based on their *energy requirements*. In particular, four demand segments are defined based on the distribution of Figure 6.6: a) Less than 6kWh, b) 6kWh-12kWh, c) 12kWh-18kWh and d) 18kWh-24kWh. The combination of charging rates with hourly slots and location of parking facility results into a complete offer set of 46 charging bundles after excluding the infeasible solutions for each given energy quantity (e.g. 24kWh in one hour). The full set of charging bundles for the examined regions is presented in Figure 6.11.

For the second level of segmentation, the arriving and departure times of simulated vehicles were used to differentiate the users according to their *time availability* at the parking facility.

Figure 6.11: Full offer set of charging bundles for the four-hour period

The third and most important dimension of segmentation is defined by users' taste heterogeneity. RM applications typically rely on the premise that different customers vary in their willingness to pay for the different attributes of the products. Modelling customer heterogeneity entails classifying the users in L segments where people within each segment have similar preferences and price responses. As it was described in Chapter 4, the empirical estimation indicated the presence of two heterogeneous latent classes: the price-conscious that are largely affected by the price of the charging bundles offered by the CSP, and the time-conscious users that are less sensitive to price and hence not as likely to be influenced by demand-side management (Latinopoulos et al., 2015a). The class-specific utility function of an individual n belonging to segment ℓ for a charging bundle j is the following:

$$\begin{aligned} U_{jn}^{\ell} = ASC_j + \beta_E^{\ell} E_{jn} + \beta_p^{\ell} p_j + \beta_{p,WBT}^{\ell}(p_j * WBT_n) + \beta_{WT}^{\ell} WT_{jn} \\ + \beta_{WT,TWD}^{\ell}(WT_{jn} * TWD_n) + \beta_{CISDE}^{\ell} CISDE_{jn} + \beta_{CISDL}^{\ell} CISDL_{jn} \\ + \beta_{CD}^{\ell} CD_j \end{aligned} \tag{6.2}$$

where E_{jn} is the required energy quantity, p_j is price, WBT_n is a dummy variable for work-based tours, WT_{jn} is the walking time from charging post to destination, TWD_n is a dummy for individuals that travel on weekdays, $CISDE_{jn}$ and $CISDL_{jn}$ are the charging induced schedule delays (early and late respectively) and CD_j is charging duration. Walking distance from the parking facility to activity destination is transformed to walking time according to the typical walking speed for urban areas (1.84 m/s or 84m/min). The majority of the coefficients that are used for the simulation are adopted from the restricted latent class model in Table B.3[72]. The coefficient for charging quantity β_E^{ℓ} is approximated by the sensitivity to final SOC (0.094/kWh), estimated by Daina (2014) while the coefficient for CISDL is calculated proportionally to CISDE based on the ratio SDL/SDE=3.68, estimated for London commuters with fixed working hours in Hess et al. (2007).

Combining the three levels of segmentation (2 latent classes, 4 discrete energy quantities and 10 dwelling periods) results in a total set of 64 customer segments (Figure 6.12). Each segment ℓ has a consideration set $C_{\ell} \subset J$ where J is the whole set of available bundles. Since these consideration sets influence the final allocation, it is assumed that the CSP has prior knowledge of them, something that is plausible with recharging data availability. These consideration sets are also allowed to overlap ($C_{\ell} \cap C_{\ell'} \neq 0 \; for \; \ell \neq \ell'$).

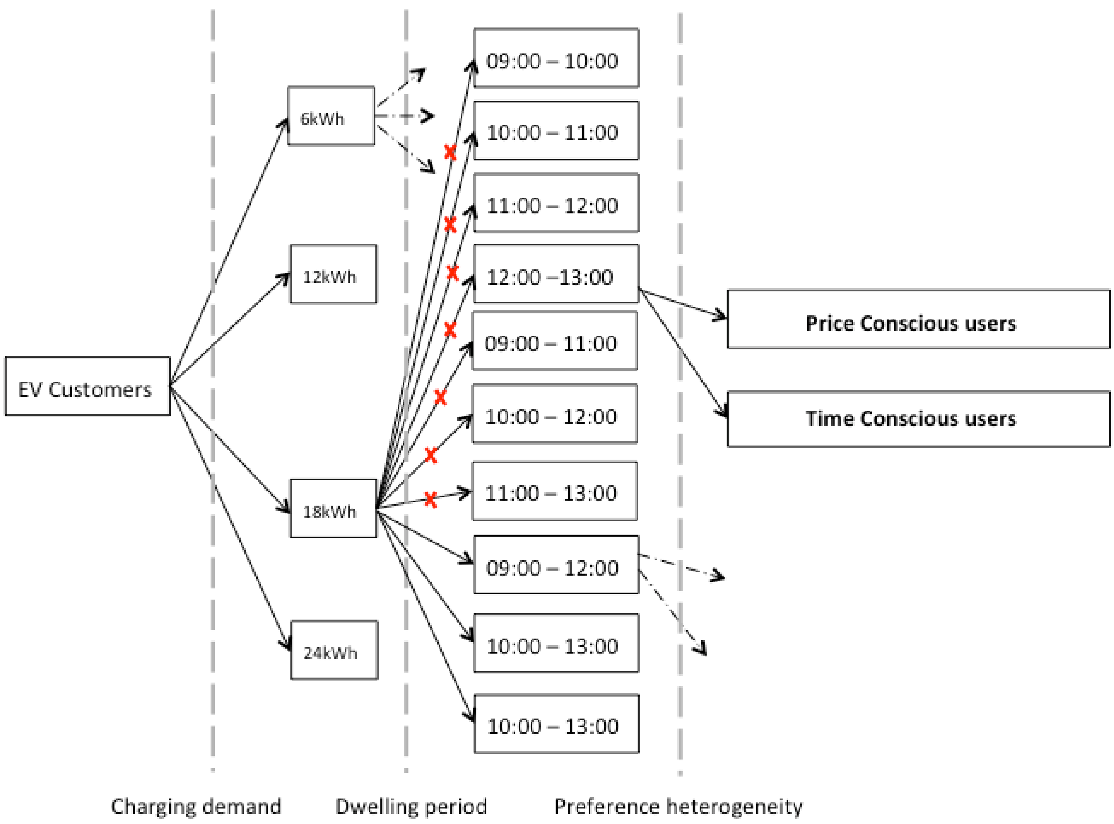

Figure 6.12: EV customer three-level segmentation

[72] The scale parameter that was estimated to reduce the variance of the error term for Panelbase respondents is not used for the simulation of charging choices. In this way, the forecasting model reflects better the reference environment (internally recruited drivers) that was considered to be closer to real behaviour

A segment-ℓ customer's choice is not affected by products outside his consideration set even if they are offered by the operator. The probability of the customer buying a bundle $j \in J$ is denoted by P_j^ℓ and is given by the following multinomial logit model:

$$P_{jn}^{\ell} = \frac{e^{U_{jn}^{\ell}}}{\sum_{k \in J} e^{U_{kn}^{\ell}} + e^{U_{0n}^{\ell}}} \tag{6.3}$$

where U_{0n}^{ℓ} is the utility he obtains by choosing the "skip" option. The "skip" option was not included in the estimation for reasons that were explained in Chapter 4. Nevertheless, for the purposes of the simulation, the alternative specific constant was calibrated so that a small proportion of individuals skip the charging choice. The effect of this calibrated parameter on the outcome of the optimization is examined through a sensitivity analysis later in the chapter.

The class membership probability for the latent class model in the simulation consists of the following parameters: gender, age, marital status, employment status, income and parental status. The consideration sets of the customer segments for the scenarios with and without V2G[73] are presented in Appendix D.

In the FCFS simulation, individuals arrive at the area sequentially and they choose among the available charging bundles in the two parking facilities. If their preferences for charging rate, time-of-day and walking time are satisfied then the charging bundle is allocated to them. The drivers' first option is the charging bundle with the higher probability among all the bundles in their consideration set. If this option is not available, they are evaluating some of the other opportunities, randomly drawn based on their respective opportunities.

After assessing a subset *J'* of their consideration set, if no option is available due to capacity limitations, they are classified as a **non-allocated** event and the simulation continues with the arrival of the next driver. On the other hand, if for any of this *J'* choice processes the utility that the EV driver obtains from buying nothing is higher than the utility from buying any of the other options, then he is withdrawn from the simulation and classified as a **non-buying** event. Once a charging bundle is **allocated**, the resources of the CSP are reduced by one charging post and a certain amount of power that is associated with the charging rate of the allocated bundle. For the purposes of this simulation, the number of assessments before the

[73] The discharging (V2G) bundles are defined later in this section

vehicle is considered as non-allocated is set to be *J'*=3.The flow chart of the described simulation process is presented in Figure 6.13.

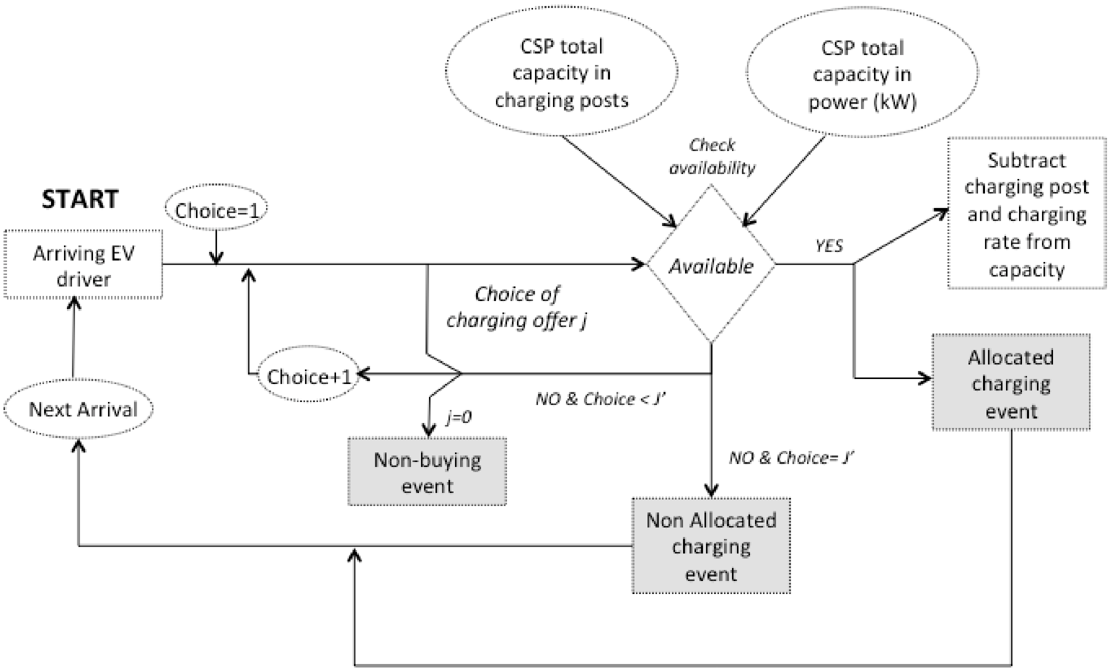

Figure 6.13: Flow chart of First-come-first-served scheduling algorithm

The prices for the NLP and LP systems are given by the following equations:

$$p_{j,NLP} = p_{hour} + p_{base} * R_j * T_j * CD_j \tag{6.4}$$

$$p_{j,LP} = p_{hour} + p_{base} * R_j * T_j * A_j * CD_j \tag{6.5}$$

where p_{hour}: is the hourly parking tariff which is assumed to be £1.00

$p_{j,NLP}$: price of charging bundle j for the non-locational pricing system

$p_{j,LP}$: price of charging bundle j for the locational pricing system

p_{base}: base price of electricity (it is assumed to be 10p/kWh)

R_j: rate factor of charging bundle j (power-intensive charging bundles are penalised with a higher factor

T_j: time factor of charging bundle j (charging bundles that include hour slots with peak load are penalised with higher factors)

A_j: area factor of charging bundle j (charging bundles that take place in the parking facility with the higher demand are penalised with a higher factor for the LP system).

The parking tariffs are reduced compared to typical rates of the examined regions. Nevertheless, when they are calculated jointly with the electricity tariff, they are representative of the actual prices. The rationale for this pricing system is that parking operators need to preserve their tariffs but at the same time the differentiation should be driven by the effect of the charging services on the grid. Besides, if electricity price is added on top of the existing tariffs, it will be quite unattractive for customers to charge their vehicles out-of-home.

The penalty factors described above are normalised so that the maximum unit price of electricity is 55p/kWh. This maximum price occurs when a charging bundle combines peak-load hour slots with a charging rate of 12kW and, for the LP system, a charging post located at the facility with the highest demand.

When the CSP estimates the expected revenues from the charging bundles that are allocated to the EV drivers, it is important to monitor the balancing between demand and supply. The power supply is negotiated in advance with the DSO and each power unit that that is not allocated for EV charging has to be reimbursed, multiplied by the imbalance factor. Imbalance costs should be higher for peak-load periods; thus, it is assumed that they are approximated by the time factor T_j. Obviously, this might differ from reality where imbalance prices depend on a power market index that reflects the value of energy traded on this particular day. However, it is a simplification that captures the temporal variation of electricity price and highlights the significance of charging demand prediction for the CSP.

As a result, the net revenue for the CSP is equal to the difference between the profit from selling the charging bundles and the imbalance costs from non-allocated capacity. The simulation results are assessed based on the following metrics (Latinopoulos et al., 2015b):

- The revenue that is generated from the allocated charging bundles
- The number of non-allocated EVs
- The remaining power (spare capacity) and the associated imbalance costs
- The remaining charging posts and the load factor of the parking facility

NLP and LP systems are compared for both regions and the potential benefits of the latter are highlighted. Combining the three scenarios for EV penetration rate and the three scenarios for the headroom of substation capacity, nine scenarios are evaluated for each pricing system and region, giving a total of 36 scenarios. The simulation metrics for these scenarios are presented in Appendix E (Tables E1-E4) and the aggregated outcomes in Table 6.1.

Table 6.1: Aggregated outcomes for the FCFS simulation of the two examined areas

Parking location	**Westfield**			**Canary Wharf**		
Capacity headroom:	0%	10%	20%	0%	10%	20%
Non Locational Pricing (NLP)						
25% EVs						
Revenue	1664	5021	4913	1625	6150	6226
Net revenue[1]	1034	2704	168	1310	3043	-1117
Parking Load Factor[2]	15.4%/8.7%	52.7%/28.2%	51.6%/28.6%	15.0%/9.6%	60.1%/40.0%	61.4%/40.1%
Power Load Factor	68.7%	48.4%	28%	73%	41.6%	22.7%
50% EVs						
Revenue	2241	9045	9643	2164	11770	11991
Net revenue	2062	7923	6209	2060	10194	5679
Parking Load Factor	19.1%/11.2%	86.0%/47.5%	88.1%/60.0%	15.7%/12.2%	94.4%/79.5%	93.5%/84.1%
Power Load Factor	88.1%	67.9%	51.7%	91.0%	73.7%	41.0%
100% EVs						
Revenue	2598	10364	13318	2347	13253	13949
Net revenue	2595	10068	10910	2345	12290	8236
Parking Load Factor	22.2%/11.9%	95.2%/53.7%	99.8%/91.7%	17.1%/13.4%	99.8%/92.7%	99.6%/99.5%
Power Load Factor	99.7%	93.5%	67.9%	99.7%	83.2%	47.0%
Locational Pricing (LP)						
25% EVs						
Revenue	1653	4648	4948	1599	6104	5977
Net revenue	1317(+)	2796(+)	935(+)	1319(=)	4329(+)	-376(+)
Parking Load Factor	12.4%/10.6%	29.2%/42.2%	27.3%/50.6%	10.0%/11.5%	29.8%/67.2%	31.1%/66.2%
Power Load Factor	65.8%	44.7%	27.8%	69.0%	41.2%	22.7%
50% EVs						
Revenue	2214	8108(-)	9478	2061	10585	11219
Net revenue	2058(=)	7120(-)	6526(+)	1931(=)	8986(-)	5697(=)
Parking Load Factor	17.6%/11.7%	67.2%/49.8%	59.0%/83.3%	13.8%/13.0%	70.0%/85.9%	67.2%/97.4%
Power Load Factor	85.7%	72.3%	50.9%	86.7%	68%	39.2%
100% EVs						
Revenue	2605	10371	13474	2406	13483	13935
Net revenue	2563(=)	9993(-)	11487(+)	2387(=)	12602(=)	9121(+)
Parking Load Factor	21.0%/11.6%	89.8%/52.2%	95.2%/92.5%	17.0%/13.2%	97.8%/92.2%	97.2%/100.0%
Power Load Factor	96.1%	89.3%	67.5%	98.0%	82.2%	46.9%

[1] The net revenue is calculated after subtracting imbalance costs for the remaining power.
[2] The two values correspond to the load factor of parking facility one and parking facility two respectively

The capacity of each parking facility in charging posts is considered equal to 625 based on information about existing availability of parking places[74] and on the assumption that there is a charging post for every parking place. Currently, the availability of charging posts is much lower (approximately 1%) but this is likely to change with increasing rates of EV sales. For economies of scale, the unit cost for charging equipment will significantly decrease for CPMs. Still, this assumption is an optimistic version for future recharging infrastructure, and a sensitivity analysis is performed for the revenue management application in section 6.6.

As expected, the scenarios with the lowest rate of EV penetration in the market generate less revenue compared to the other scenarios. For increasing power capacity headroom, the revenue from allocating the charging bundles to EV customers increases. The latter does not hold for cases where the incoming demand is already satisfied with the existing capacity, where revenue remains rather stable even with increased power availability. For example, when locational pricing is applied in Westfield area, a shift from 0% to 10% capacity headroom gives £3000 extra revenue, whereas a shift from 10% to 20% capacity headroom only gives £300 extra revenue.

Another strong assumption for the simulations above is that the CSP reserves all the spare power capacity in his bilateral negotiations with the DSO. While this is desired for peak periods, it can result in a large proportion of off-peak capacity not being allocated to EV customers, thus incurring significant imbalance costs. For example, the net revenue is negative for the 25% EVs - 20% headroom - Canary Wharf scenario because the demand is low and only 22.7% of the contracted power load is utilised. Consequently, the CSP may generate £6,226 from selling a certain set of charging bundles but at the same time, he has to compensate £7343 to the DSO for over-predicting the required amount of energy. The strategic decision of how much power is required for each time period is also evaluated through sensitivity analysis in the revenue management section.

For both areas, the first parking facility is located closer to the centroid of the examined zone and hence the average distance from the individuals' destinations is smaller compared to the second parking facility. This explains why the choice probabilities disproportionally allocate more charging demand to parking facility one for all NLP scenarios. With the implementation

[74] For example, there are four underground public car parks around the area of Canary Wharf with a total of 2,500 parking spaces. (http://canarywharf.com/getting-here/parking/). Consequently, it can be assumed that each parking facility has, on average, 625 parking spaces.

of LP, EV drivers are penalised for using the high demand facility (i.e. parking facility one) and, thus, charging events in the less congested facility are promoted.

For relatively constrained scenarios (25% EVs - 0% headroom, 50% EVs - 0% headroom, 50% EVs - 10% headroom and all the 100% EVs scenarios) the Tables in Appendix E show that revenue changes fluctuate, with the general trend being that revenue marginally increases for parking facility one and marginally decreases for parking facility two. This can be attributed to the fact that drivers choosing the former pay more for the same service while the exact opposite occurs for the latter. At the same time, non-allocated power capacity (and subsequently imbalance costs) marginally increases for parking facility one and marginally decreases for parking facility two, since those that change their decision reduce the power load factor from the first location and increase that of the second. The balance of gains and losses is either positive or close to zero for the majority of these scenarios (10/13) as it is indicated with the signs inside the brackets in Table 6.1.

On the contrary, for relatively non-constrained scenarios (i.e. either all or the majority of charging events are successfully allocated), the opposite phenomenon is observed. In other words, simulation results suggest marginal revenue decreases for the high demand parking facility and marginal revenue increases for the low demand parking facility. Although this means that income from selling charging bundles diminishes with LP implementation, net revenue significantly grows, especially for the 25% demand scenarios. A possible explanation for this reduction of imbalance costs is that customers prefer to charge during peak periods at the second parking facility rather than during off-peak periods at the first parking facility and this behavioural shift is feasible due to the high availability of spare capacity.

Irrespective of the underlying process, LP provides improved net revenue performance for the majority of the examined scenarios. Nevertheless, if the objective of the CSP is to maximise revenue for the wider area, the choice of pricing strategy (NLP or LP) will affect the disaggregate revenue margins for the concerned parking operators. In cases where charging infrastructure is limited, LP could function as a spatial management tool to alleviate fully occupied facilities and assign a part of the exceeding charging demand to less congested facilities.

The problem of limited power capacity for peak demand periods could be addressed with the application of Vehicle-To-Grid techniques, as they were described in Chapter 5. In this way, plugged-in vehicles with low energy requirements are potential storage units with the ability to provide electricity to the CSP when it is mostly needed.

In order to assess the benefits of V2G, the first scenario (25% EVs and 0% capacity headroom) is selected because of its higher proximity to demand forecasts and due to the fact that the impossibility of charging during the peak period is ideal for the evaluation of V2G.

The preferences for V2G services were not directly estimated in Chapter 4 because conveying the required information for the SP exercise would be a quite complex task and it would compromise the validity of the estimated parameters. Nevertheless, future research should aim to include V2G scenarios in choice experiments about charging behaviour, targeting if possible to respondents that have already some experience with the associated technology.

For the simulations of this chapter, the following assumptions are made:

- The segmentation that is based on the drivers' energy requirements is modified in order to take into account customers that are likely to discharge their vehicle's battery and sell electricity back to the grid. In particular, individuals that have minimal driving needs (<1kWh/day) evaluate a set of 14 charging alternatives with negative charging rates and negative prices. The discrete energy quantity that is delivered with these options is 6kWh and the complete offer set of the CSP now consists of 60 charging bundles.
- The sensitivity to energy amount and the sensitivity to price remain the same as for conventional charging services. However, the fact that the respective attributes have now the opposite sign results into a negative marginal utility for energy and a positive marginal utility for selling price. It is likely that drivers will demonstrate an asymmetry in their charging and discharging behaviour. Moreover, the battery degradation from the repeated charging/discharging cycles could incur an extra disutility for EV owners. Since it was not possible to estimate these effects, and no information was available from existing studies, a sensitivity analysis of the energy-related coefficient is presented in the revenue management section of this chapter.

The simulation metrics that were mentioned earlier are compared for the scenario without V2G and the scenario with V2G and the results are demonstrated in Figures 6.14-6.21. All figures contain four subplots that combine the two pricing systems with the two areas of interest.

Figures 6.14 and 6.15 illustrate the remaining power in kW after allocating the charging requests.

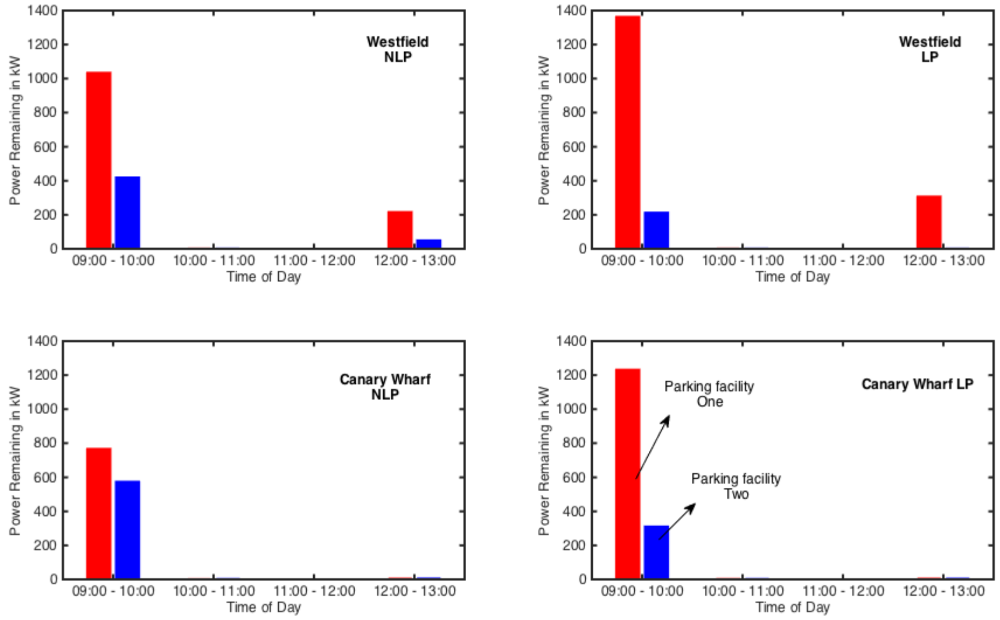

Figure 6.14: Spare power capacity for each hour slot, pricing system and area

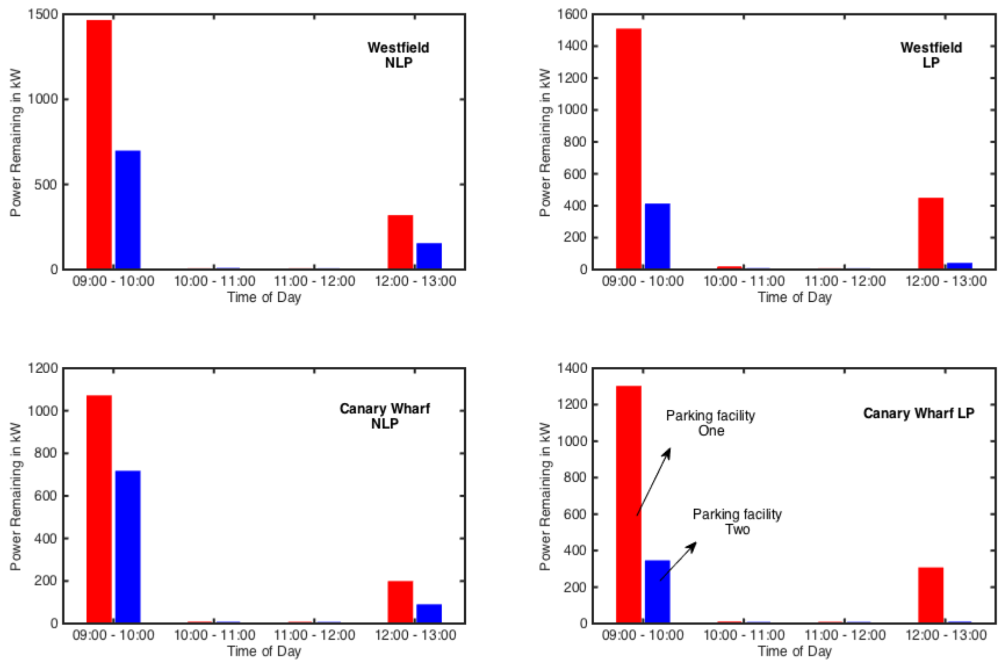

Figure 6.15: Spare power capacity for each hour slot, pricing system and area with V2G

Without V2G, the headroom capacity for the intermediate hour slots is either very low (10:00-11:00) or zero (11:00-12:00). As a result, there is no remaining power for this period while the remaining power for the first and the fourth hour slots could be attributed to the fact that some drivers preferred longer charging durations and hence they could not be allocated with a charging bundle. When V2G services are provided, power is again fully consumed during peak periods, even though some plugged-in vehicles contributed with additional capacity units. On the other hand, the portion of customers that sold electricity to the grid increased power availability during the off-peak periods.

Figures 6.16 and 6.17 show that the parking load factor has increased after V2G implementation due to the combination of two factors: First, drivers that are willing to sell electricity to the CSP are always allocated with a charging post because they are not affected by the power capacity at the time of their arrival. Second, the increased power availability from discharging vehicles enables the accommodation of additional charging customers, relative to the scenario without V2G.

For the same reason, the number of vehicles that are not allocated with a charging post significantly reduces when V2G services are considered (Figures 6.18 and 6.19). It has to be noted here that for the investigated level of EV penetration in the market, the capacity in charging posts is never a limiting factor for the allocation of charging events. The reason the vehicles below could not be accommodated is the restricted power capacity, especially for the intermediate hour slots.

Finally, the two last sets of graphs (Figures 6.20 and 6.21) demonstrate the revenue that is generated by the CSP, broken down by parking facility and hour of operation. It can be seen that the marginal revenue for peak periods has significantly increased with the introduction of V2G. Although the CSP has to pay the drivers that provide electricity to the network, V2G prices are always lower from charging prices and their mutual effect is positive. Specifically, it is assumed that time and area factors remain the same for discharging while rate factors are calculated inversely to conventional charging bundles.

The analysis in this section describes the “uncontrolled” charging scenario when EV drivers select their charging characteristics based on the latent class choice model developed in Chapter 4. Therefore, it is more sophisticated than the dumb charging approach in terms of capturing the spatiotemporal distribution of demand. However, in FCFS scheduling, there is no charging coordination applied from the CSP. If the preferred option is available it is automatically allocated to the driver. This lack of control from the operator’s side might lead to increased proportions of non-allocated vehicles and suboptimal revenue performance.

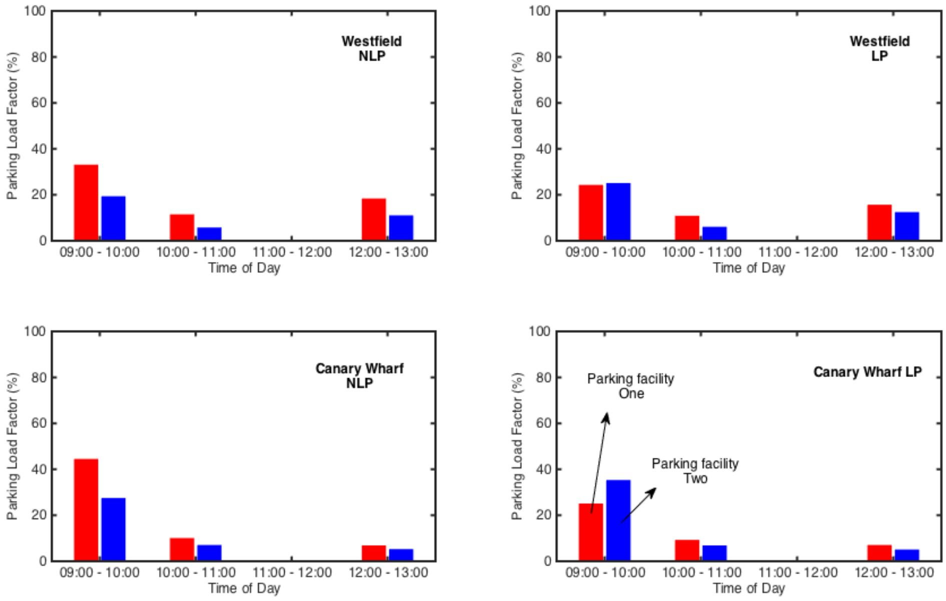

Figure 6.16: Parking load factor (%) for each hour slot, pricing system and area

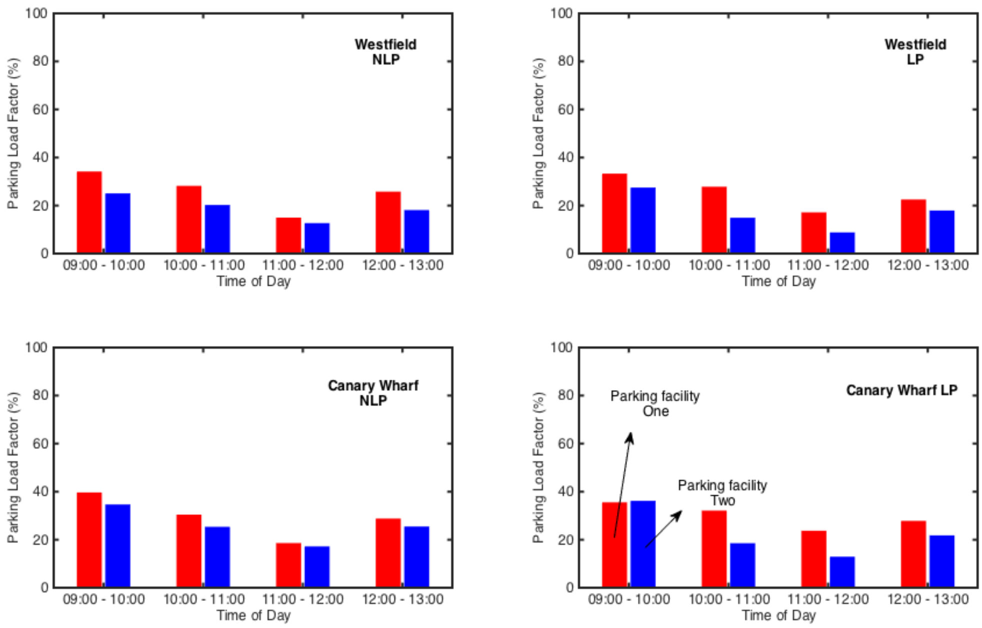

Figure 6.17: Parking load factor (%) for each hour slot, pricing system and area with V2G

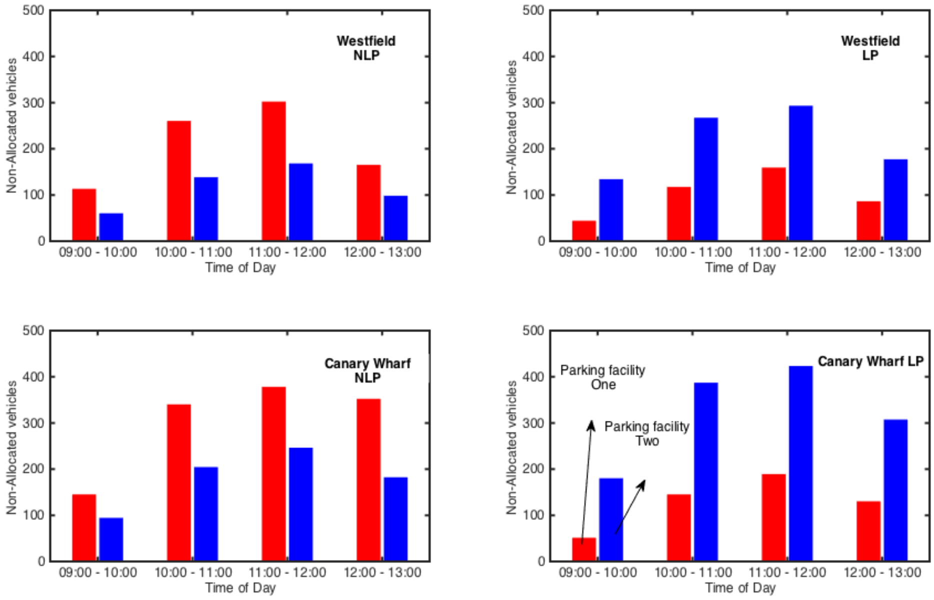

Figure 6.18: Number of non-allocated vehicles for each hour slot, pricing system and area

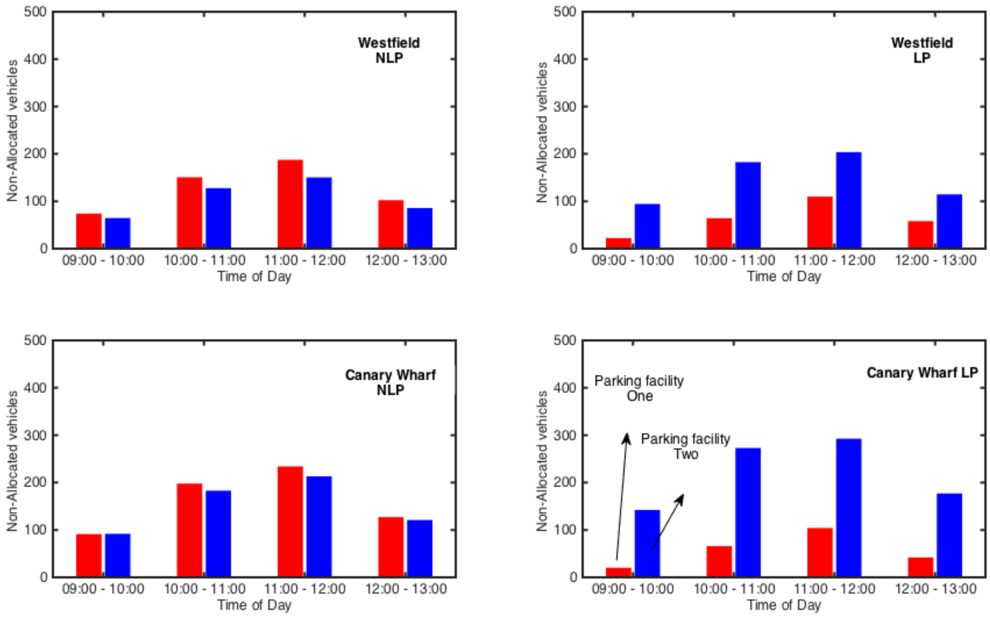

Figure 6.19: Number of non-allocated vehicles for each hour slot, pricing system and area with V2G

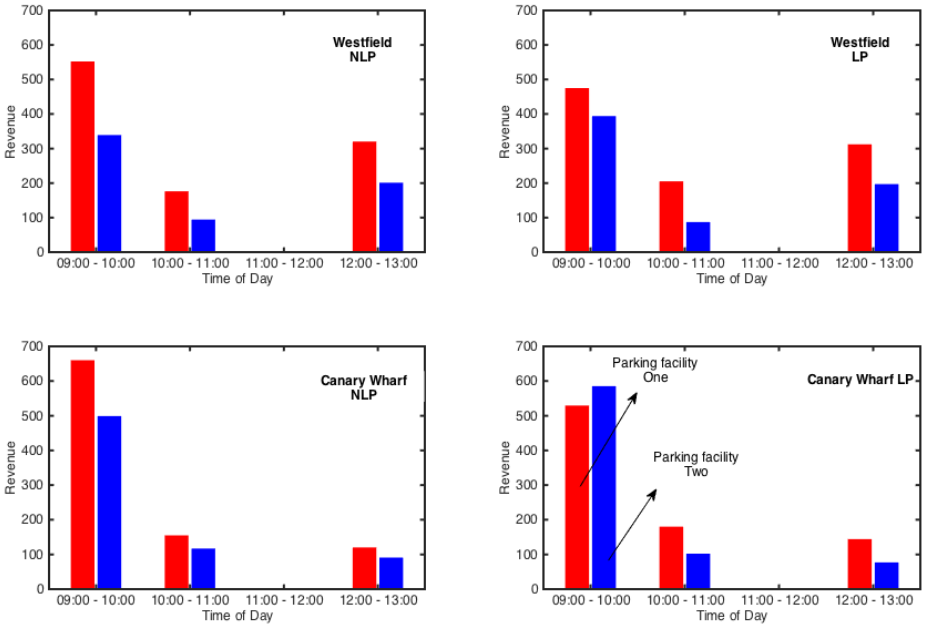

Figure 6.20: Revenue (in £) from allocated charging bundles for each hour slot, pricing system and area

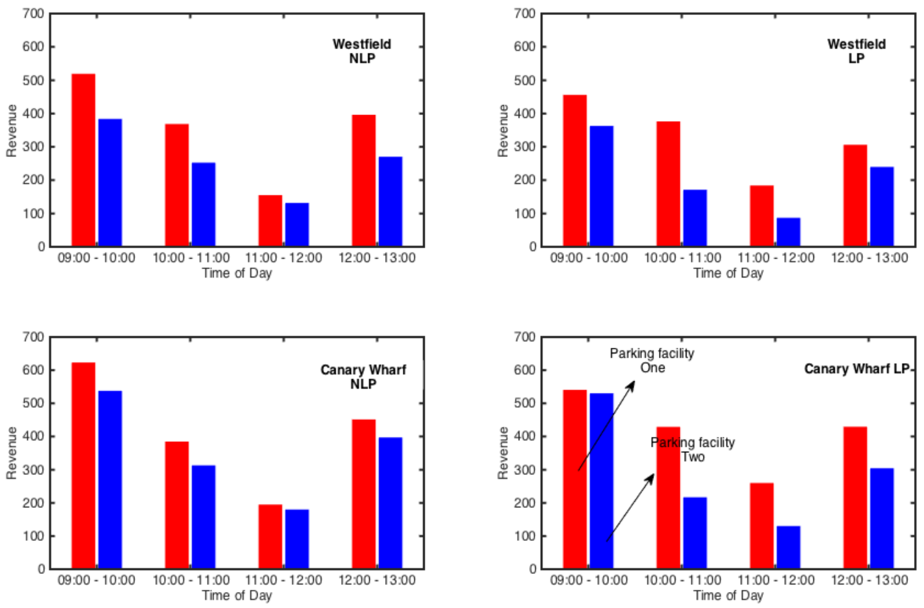

Figure 6.21: Revenue (in £) from allocated charging bundles for each hour slot, pricing system and area with V2G

Moreover, the pricing strategies that have been developed to incentivize off-peak (in time and space) and low-rate charging are not implicitly affected by choice parameters. In the next subsection, a pricing optimisation is applied in order to identify the combination of prices for the charging bundles that result into the maximum revenue for the CSP. Its choice-based formulation allows the offline optimisation of the daily tariff schedule, based on the anticipated shares among the various latent classes of EV drivers.

Nevertheless, the online dynamic control of charging demand, as it arrives at the system, is not modelled until section 6.6. At this point, the SDCP method that was introduced in 5.3.3 is employed. This heuristic dynamically allocates EV customers according to their preferences, their arrival time at the reservation system and the remaining capacity of the CSP at this time. The optimised prices from the previous model are used as input variables for this network revenue management approach where the decision variable is the set of charging bundles that should be made available to each customer segment for every step of the reservation period. The results are compared with the uncontrolled FCFS scenario and a set of sensitivity analyses is performed to evaluate the capabilities of this modelling tool.

6.5 Latent class choice-based optimal pricing for out-of-home charging services

While in choice modelling literature there has been an increasing interest about heterogeneity in taste preferences and the development of latent class models, their application in revenue management is not very common. Typically, researchers make the assumption of demand homogeneity. Segmentation and class-specific parameters have been recently incorporated in RM with the introduction of the CDLP formulation that was presented in Chapter 5. Méndez-Díaz et al. (2012) developed a latent-class-based optimisation, which they proved to be NP-hard for overlapping consideration sets of the customer segments, and hence, they used a branch-and-cut approximation method to solve the CDLP. Hetrakul and Cirillo (2014) suggested an optimisation framework for joint pricing and seat allocation in the railway industry, capturing passenger behaviour with both MNL and LC choice models.

The pricing optimisation framework assumes that the CSP maximises the expected revenue for the four-hour period and suggests a price strategy which varies based on the charging bundle characteristics. The final solution should satisfy the constraints for the two-dimensional capacity, i.e. 8 constraints for charging post availability and 8 constraints for power availability (one for each hour slot and each parking facility). The decision variables are the prices of the offered charging bundles (p_j), which are 46 for the scenario without V2G and 60 for the scenario with V2G, as they were presented in the previous section.

The optimisation problem for EV drivers that are segmented in price-conscious and time-conscious, based on the latent class model, is formulated as follows:

$$\max_{p_j} Revenue = D^{EV}[\sum_{j=1}^{J}\{\sum_{\kappa=1}^{K} P_n(\kappa|z_n)\, P_n(j|X_i, Z_n, \beta_\kappa; \kappa)p_j\}] \\ - \left[Y - D^{EV}B\sum_{\kappa=1}^{K} P_n(\kappa|z_n)\, P_n(j|X_i, Z_n, \beta_\kappa; \kappa)\right]p^I \quad (6.6)$$

subject to

- Capacity constraints

$$D^{EV}A\sum_{\kappa=1}^{K} P_n(\kappa|z_n)\, P_n(j|X_i, Z_n, \beta_\kappa; \kappa) \leq X \quad (6.7)$$

$$D^{EV}B\sum_{\kappa=1}^{K} P_n(\kappa|z_n)\, P_n(j|X_i, Z_n, \beta_\kappa; \kappa) \leq Y \quad (6.8)$$

- Price policy constraints

$$p_j^- \leq p_j \leq p_j^+ \quad (6.9)$$

where:

D^{EV} is the total demand for the examined area or the number of EVs that request a charging bundle,

X is the capacity in charging posts

Y is the available power

p^I is the vector of time-dependent imbalance prices

A and B are the charging post and power incidence matrices indicating when a charging bundle consumes a unit from the respective capacity dimension and

p_j^-, p_j^+ are the minimum and maximum prices for each charging bundle

The objective function can be separated into two parts: The first one is the generated revenue for the CSP, which is equal to the total demand multiplied by the probability of purchasing charging bundle j and its price. Since charging preferences are modelled with a latent class model, this probability is equal to the probability of belonging to one of the two segments identified in Chapter 4, multiplied by the conditional probability of purchasing j option. The second part represents the imbalance cost, which is the product of the remaining power capacity and the respective imbalance price. The summation of these two parts gives the net revenue that is maximised here.

Capacity constraints are intuitive since the allocated electric vehicles should always be less or equal to the available charging posts while their charging requirements should not exceed the available power capacity. Finally, price policy constraints express the fact that prices should be limited by lower and upper bounds. Minimum prices are set to zero (maximum for the V2G scenario) whereas maximum prices depend on the characteristics of the charging bundles and they are slightly increased compared to the prices that were calculated for the FCFS simulation.

The formulation is a constrained nonlinear programming problem. Nonlinearity is attributed to the fact that the decision variables are included in the exponential term of the choice probability. Since the objective function and the constraints are non-convex, the resulting problem is hard to solve with standard optimisation algorithms. For this reason, two different methods are applied to validate that the final outcome is a global minimum: optimisation with a genetic algorithm (GA) and the Global Search algorithm[75].

Genetic algorithms have their foundations on the evolutionary behaviour of biological systems (Reid, 1996). Classical algorithms generate a single potential solution at each iteration while GAs generate a population of candidate solutions, with the best candidate approaching an optimal solution. These populations are generated based on their predecessors after a series of stochastic transition operators are applied. In particular, the most significant of these operators are:

- Selection: a group of individuals (*parents*) is selected from the current population according to their fitness values and their vector entries (*genes*) are used to create *children* for the next population

[75] Traditional optimization methods were tested and got "stuck" in different local minima. The probabilistic nature of the solution with GA is one of the reasons that this evolutionary approach is not contained by local minima. The Global Search Algorithm is used as corroborating evidence that the previous solution is a global optimum.

- Crossover: Children are generated by combining the genes from a pair of parents
- Mutation: Children are generated after applying random changes to a single parent

The maintenance of such populations plays a pivotal role in reducing the probability of converging to a local solution rather than a global one. Another difference between classical algorithms and GAs is that the former follow deterministic methods to select points sequentially, whereas the computations that take place for the latter include random number generators. Constraints are handled with penalty functions (Kalyanmoy, 2000). If a candidate solution is feasible, then its penalty function is the fitness function. On the other hand, if a candidate solution is infeasible, its penalty function is the maximum fitness function among feasible solutions augmented by a sum of the constraint violations of the particular solution. In this way, infeasible candidates are extinguished before the generation of new feasible candidates.

The optimization is performed with the genetic algorithm of the Global Optimization Toolbox in MATLAB 2015. The default value for the population size is 20, the fraction of the population that is generated by the crossover function is 80% and the fraction in each subpopulation that migrates to a different subpopulation is 20%. The Global Search algorithm in MATLAB generates a set of initial points using a scatter-search algorithm and it applies a local solver to find the optima in the basins of attraction[76] for each of these points. Running the optimisation with the global search algorithm, the solution that was attained was very close to the solution from the GA-based optimisation, thus, it could be safely presumed that it is a global minimum[77]. The results from the optimisation are presented in Table 6.2.

The net revenue improvements for the two areas, with and without V2G services, are presented at the bottom of the table. The penetration rate of EVs for the optimisation was assumed to be equal to 25%. However, the algorithm could not locate feasible solutions for the 0% capacity headroom scenarios that would accommodate all the incoming demand. Therefore, the prices have been optimised for the 20% capacity headroom scenario and they will be considered as the basic tariff schedule for the dynamic allocation of next section.

[76] A basin of attraction is the set of initial points that lead to the same local minimum for steepest descent
[77] The randomness in the generation process of the GA algorithm results into slightly different values each time the optimisation is performed, therefore an exact match of the solutions is difficult to achieve.

Table 6.2: Optimised prices for charging bundles and net revenue improvements (£) for the two areas and for scenarios with and without V2G

Charging bundle #	Parking Facility	Charging Duration	Rate (kW)	Westfield		Canary Wharf	
				Without V2G	With V2G	Without V2G	With V2G
1	**1**	**09:00-10:00**	**6**	£1.25	£0.94	£1.26	£0.39
2	**2**	**09:00-10:00**	**6**	£1.26	£1.13	£1.26	£1.04
3	**1**	**10:00-11:00**	**6**	£2.26	£2.22	£2.10	£0.89
4	**2**	**10:00-11:00**	**6**	£2.27	£1.56	£2.17	£1.06
5	**1**	**11:00-12:00**	**6**	£2.96	£2.74	£2.14	£1.60
6	**2**	**11:00-12:00**	**6**	£2.96	£2.87	£2.21	£0.84
7	**1**	**12:00-13:00**	**6**	£1.76	£1.64	£1.56	£1.34
8	**2**	**12:00-13:00**	**6**	£1.76	£1.75	£1.02	£0.70
9	**1**	**09:00-11:00**	**3**	£1.26	£1.00	£1.26	£0.33
10	**2**	**09:00-11:00**	**3**	£1.26	£0.93	£1.26	£0.83
11	**1**	**10:00-12:00**	**3**	£1.87	£1.71	£1.45	£1.55
12	**2**	**10:00-12:00**	**3**	£1.87	£1.51	£1.81	£0.85
13	**1**	**11:00-13:00**	**3**	£1.69	£1.48	£1.59	£1.16
14	**2**	**11:00-13:00**	**3**	£1.69	£1.60	£1.53	£0.79
15	**1**	**09:00-10:00**	**12**	£2.50	£4.01	£4.16	£1.02
16	**2**	**09:00-10:00**	**12**	£2.64	£2.55	£4.23	£3.96
17	**1**	**10:00-11:00**	**12**	£2.71	£5.61	£1.26	£1.71
18	**2**	**10:00-11:00**	**12**	£3.68	£6.14	£1.13	£0.92
19	**1**	**11:00-12:00**	**12**	£3.92	£6.40	£0.82	£0.53
20	**2**	**11:00-12:00**	**12**	£5.92	£7.70	£3.15	£1.28
21	**1**	**12:00-13:00**	**12**	£4.33	£5.47	£1.18	£5.34
22	**2**	**12:00-13:00**	**12**	£4.29	£5.15	£1.33	£5.06
23	**1**	**09:00-11:00**	**6**	£2.86	£2.35	£3.52	£2.14
24	**2**	**09:00-11:00**	**6**	£2.64	£2.04	£3.53	£2.50
25	**1**	**10:00-12:00**	**6**	£3.89	£3.83	£1.38	£2.28
26	**2**	**10:00-12:00**	**6**	£4.62	£2.83	£1.57	£2.00
27	**1**	**11:00-13:00**	**6**	£4.23	£4.72	£1.07	£2.41
28	**2**	**11:00-13:00**	**6**	£4.25	£3.85	£2.20	£3.37
29	**1**	**09:00-13:00**	**3**	£2.61	£1.57	£2.91	£1.67
30	**2**	**09:00-13:00**	**3**	£2.94	£1.42	£2.94	£2.13
31	**1**	**09:00-12:00**	**6**	£3.78	£4.84	£3.63	£1.40
32	**2**	**09:00-12:00**	**6**	£3.43	£5.95	£3.92	£2.09
33	**1**	**10:00-13:00**	**6**	£4.94	£5.97	£1.65	£4.03
34	**2**	**10:00-13:00**	**6**	£4.30	£5.99	£1.64	£4.91
35	**1**	**09:00-11:00**	**12**	£2.14	£4.81	£2.77	£2.23
36	**2**	**09:00-11:00**	**12**	£2.11	£9.01	£2.17	£6.97
37	**1**	**10:00-12:00**	**12**	£5.05	£12.48	£1.03	£16.64
38	**2**	**10:00-12:00**	**12**	£16.76	£12.54	£16.42	£15.30
39	**1**	**11:00-13:00**	**12**	£9.22	£14.09	£8.53	£7.04
40	**2**	**11:00-13:00**	**12**	£10.05	£12.09	£1.27	£7.43
41	**1**	**09:00-12:00**	**8**	£4.27	£9.05	£8.50	£3.49
42	**2**	**09:00-12:00**	**8**	£5.21	£7.78	£5.96	£8.74
43	**1**	**10:00-13:00**	**8**	£9.42	£10.49	£0.47	£0.45
44	**2**	**10:00-13:00**	**8**	£8.13	£9.70	£6.66	£1.85
45	**1**	**09:00-13:00**	**6**	£6.93	£6.75	£4.78	£1.83
46	**2**	**09:00-13:00**	**6**	£5.20	£5.67	£4.70	£4.41
47	**1**	**09:00-10:00**	**-6**	-	£0.06	-	£0.25
48	**2**	**09:00-10:00**	**-6**	-	£0.16	-	£0.47
49	**1**	**10:00-11:00**	**-6**	-	£0.29	-	£0.29
50	**2**	**10:00-11:00**	**-6**	-	£0.20	-	£0.94
51	**1**	**11:00-12:00**	**-6**	-	£0.11	-	£0.70
52	**2**	**11:00-12:00**	**-6**	-	£0.37	-	£1.43
53	**1**	**12:00-13:00**	**-6**	-	£0.17	-	£0.14
54	**2**	**12:00-13:00**	**-6**	-	£0.25	-	£0.48
55	**1**	**09:00-11:00**	**-3**	-	£0.04	-	£0.43
56	**2**	**09:00-11:00**	**-3**	-	£0.04	-	£0.38
57	**1**	**10:00-12:00**	**-3**	-	£0.27	-	£0.41
58	**2**	**10:00-12:00**	**-3**	-	£0.07	-	£0.79
59	**1**	**11:00-13:00**	**-3**	-	£0.33	-	£0.20
60	**2**	**11:00-13:00**	**-3**	-	£0.40	-	£0.48
Revenue Improvement				£934	£1,804	£2220	£2,527

It can be observed that there are significant improvements compared to the respective net revenues of the FCFS simulation in Table 6.1. These net revenue gains are mainly driven by the inclusion of imbalance costs at the objective function of the optimisation. Therefore, while the gross profit from selling the charging bundles has relatively small changes compared to the uncontrolled case, the EVs are allocated in such a way that the remaining power, especially for peak hours, is minimised. Figures 6.22-6.24 demonstrate the optimised prices classified based on the different charging characteristics. The results are graphically presented only for the Westfield area because the relative relationships are similar for the Canary Wharf area.

In Figure 6.22 it can be observed that as the charging rates (in kW) increase, the price of the charging bundles increase as well. The discharging tariffs are presented in negative terms because they correspond to the amount that the CSP has to compensate to EV drivers for offering V2G services. Their relative magnitude to charging prices is quite small because they are offset by the parking price component. Practically, these prices could be beneficial for EV drivers if they have cheaper charging opportunities at home as well as long-term contracts with the CSP so that they provide electricity back to the grid on a regular basis. For low rates (3kW-6kW) the optimisation for the scenario without V2G gives higher prices while this relationship is slightly reversed for higher rates (8kW-12kW). Probably this can be attributed to the fact that higher rates yield higher marginal benefits and hence they are more suitable to balance the revenue losses from buying V2G energy.

In Figure 6.23, prices are classified by charging duration and it can be seen that there is a general increasing trend, with the higher prices, however, occurring for two-hour charging bundles. The reason this is happening is that longer charging durations are associated with lower charging rates while the most expensive two-hour bundles are the ones that offer 12kW rates. As with Figure 6.22, the prices for the scenario where V2G services are included are higher, especially for the power-intensive situations. Moreover, discharging prices seem to increase for higher charging durations. This could be perceived as a reward to those drivers that are willing to have their vehicles plugged-in, and hence available to the CSP, for longer periods. The gains for the drivers by selling V2G services are similar to the findings of Hartmann and Ozdemir (2011) (i.e. 0.68€/day).

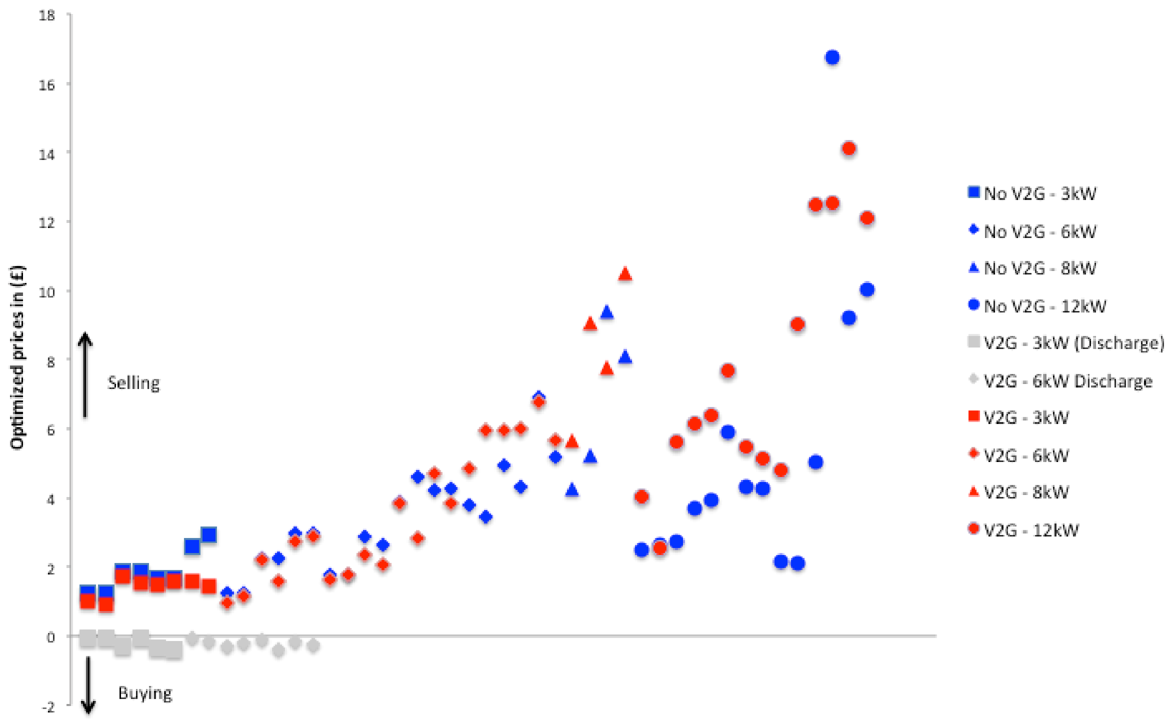

Figure 6.22: Scatter plot of charging bundle prices classified by power rate

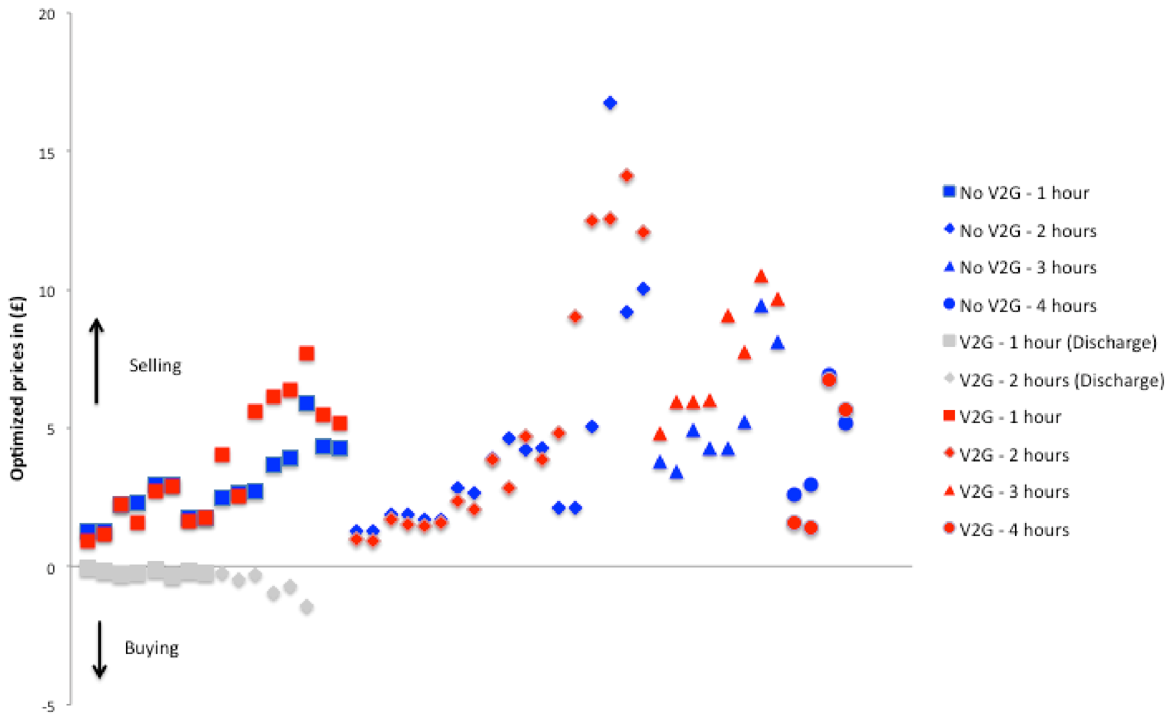

Figure 6.23: Scatter plot of charging bundle prices classified by charging duration

Finally, Figure 6.24 distinguishes those charging bundles that include the peak hour slot (i.e. 11:00 am – 12:00 pm) from those who don't. In their majority, the former are more expensive in order to capture the lack of resources and function as an incentive to shift EV customers to other options.

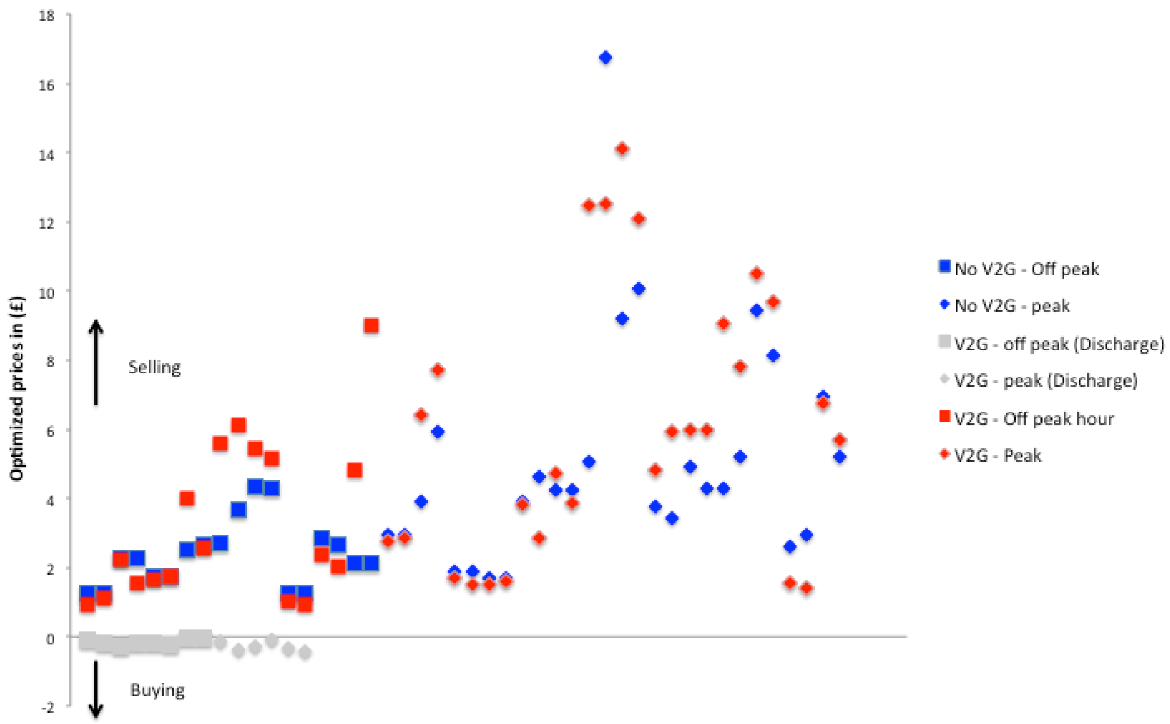

Figure 6.24: Scatter plot of charging bundle prices classified by time of charging event (peak and off-peak)

The CSP could adopt the prices that are presented in this section, and use this optimal tariff schedule as a starting point for his dynamic allocation strategy that is presented in the following section.

6.6 Dynamic capacity allocation for out-of-home charging services

6.6.1 Model formulation

The model set-up and notation are broadly consistent with Meissner et al. (2013). The booking horizon is assumed to be discrete and consists of T steps, indexed by t. The reservation period opens at t=T and closes at time t=0 when the parking facilities start to operate and reservations for next day are made available. It is a normal convention to assume that these steps are discretised in such a way that the probability of more than one driver arriving at each step is negligible. The test network of this section has a total of $m_1 + m_2$ resources indexed by i (m_1 in the first parking lot and m_2 in the second). Moreover, the CSP offers n "charging bundles" (indexed by j) each of which consumes a set of the resources and generates revenue to the operator, equal to r_j.

Furthermore, α_{ij} is used to indicate when a bundle j uses resource i ($\alpha_{ij} = 1$) and when not ($\alpha_{ij} = 0$). The set of all possible α_{ij} is represented by the *charging post incidence* matrix **A**. Likewise, **B** is the *power incidence* matrix. The elements of this matrix b_{ij} indicate when charging bundle j does not consume resource i ($b_{ij} = 0$) and the power in kW utilised, when product j consumes resource i ($b_{ij} = \alpha_{ij} \mathrm{P_{EV,j}}$) where $\mathrm{P_{EV,j}}$ is the recharging rate of bundle j. Also, power and charging post capacity on resource i at time t are denoted as $x_{i,t}$ and $y_{i,t}$ respectively. In vector form the capacities are $\vec{x}_t$ and $\vec{y}_t$, so the initial set of capacities at time T is $\{\vec{x}_t, \vec{y}_t\}$. The state of the network is described with respect to the remaining capacities in both dimensions for all the resources by the following matrix: $(\vec{x}_t, \vec{y}_t) = ([x_{1,t}, \dots, x_{m_1,t}, \dots x_{m_1+m_2,t}], [y_{1,t}, \dots, y_{m_1,t}, \dots y_{m_1+m_2,t}])$. When one unit of bundle j is sold, the state of the network transforms to $(x - A_j, y - B_j)$. A_j and B_j are used to represent the charging and the power incidence vector for product j respectively.

Revenue management requires the market to be segmented in order for the differentiated products to be attractive for varying customer classes. Therefore, the incoming reservations are grouped in $L \coloneqq \{1, \dots, \ell, \dots, L\}$ segments with *distinct recharging behaviours*. The probability of a reservation for a charging post to arrive at each step is λ. An EV driver belongs to segment ℓ with probability p_ℓ. The probability of a reservation arrival from a specific segment ℓ is λ_ℓ and, as a result, $\lambda_\ell = p_\ell \lambda$ and if it is assumed that $\sum_\ell p_\ell = 1$ then $\lambda = \sum_\ell \lambda_\ell$. It is considered that arrival rates and the segment mix are homogeneous and remain constant through the booking horizon. Therefore, a segment-specific arrival rate is calculated according to the characteristics of the synthesised population and the segment mix is derived from the class membership probabilities estimated in Chapter 4. Then, at the end of this section, we perform a sensitivity analysis for the segment mix and examine what is the impact on revenue for scenarios with, and without V2G.

For each step of the booking horizon, the CSP offers a subset S of his recharging products, referred to as the *offer set*. The decision variable of the optimisation problem is which offer set should be given at each step t so that revenue is maximised. Given the charging bundle availability, the driver decides either to reserve a bundle j in offer set S or to skip the purchase. The “skip” option here can be translated in several ways: cancellation of the trip/activity, shift to public transport or conventional ICE vehicle, reservation with other CSP etc. Irrespective of the offer set S, this option is available to the driver at every step and it is indexed by 0.

Let S_ℓ be the intersection of offer and consideration set for segment ℓ. Then if $P_j^\ell(S)$ is the probability defined in equation 6.3, it can be inferred that $P_j^\ell(S) = P_j^\ell(S_\ell)$ and the following vector is defined: $\vec{P}^\ell(S) = [P_1^\ell(S_\ell), \dots, P_n^\ell(S_\ell)]$. For a given step of the booking horizon where set S is offered, the probability of the CSP selling bundle j is $P_j(S) = \sum_{\ell} p_\ell P_j^\ell(S)$ and the probability of selling nothing is $P_0(S) = 1 - \sum_{j \in S} P_j(S)$. Using vector notation, the above become $\vec{P}(S) = [P_1(S), \dots, P_n(S)]$ and $\vec{P}(S) = \sum_{\ell} p_\ell \vec{P}^\ell(S)$. If the expected revenue generation from a reservation arrival is $\vec{R}(S)$ and from a segment- ℓ reservation arrival $\vec{R}^\ell(S)$ then:

$$\vec{R}(S) = \sum_{j \in S} r_j P_j(S) \ \ and \ \ \vec{R}^\ell(S) = \sum_{j \in S_\ell} r_j P_j^\ell(S_\ell) \tag{6.10}$$

Moreover, if $Q_i^x(S)$ is the conditional probability of using a charging post on resource i and $Q_i^y(S)$ is the conditional probability of using a unit of power capacity on resource *i,* the following vectors of capacity consumption probabilities can be defined (for all customers and segment-ℓ customers respectively):

$$\vec{Q}^x(S) = A\vec{P}(S) \ \ and \ \ \vec{Q}^{x,\ell}(S) = A\vec{P}^\ell(S) \tag{6.11}$$

$$\vec{Q}^y(S) = B\vec{P}(S) \ \ and \ \ \vec{Q}^{y,\ell}(S) = B\vec{P}^\ell(S) \tag{6.12}$$

To determine optimal control using a dynamic program, the *Bellman equation* is applied as follows:

$$\begin{gathered} V_t^{DP}(\vec{x}_t, \vec{y}_t) = \max_{j \in S}\{\sum_{j \in S} \lambda P_j(S)(r_j + V_{t-1}(\vec{x}_t - A_j, \vec{y}_t - B_j)) + \\ (\lambda P_0(S) + 1 - \lambda) V_{t-1}(\vec{x}_t, \vec{y}_t)\} \end{gathered} \tag{6.13}$$

where $V_t^{DP}(\vec{x}_t, \vec{y}_t)$ is the maximum expected revenue to go when the remaining capacity is $(\vec{x}_t, \vec{y}_t)$ and there are still *t* steps in the booking horizon. The first part of the equation is the expected revenue by selling bundle *j* in step *t* and the maximum expected revenue to go, from the next step until the end of the booking horizon, when one unit of *j* is removed from the CSP's stock. The second part of the equation is the maximum expected revenue to go from the next step when the capacity remains unchanged for two possible reasons: a) there is a reservation arrival but the EV driver chooses the "skip" option or b) there is no arrival at all. The boundary conditions of the problem are $V_0^{DP}(\vec{x}_0, \vec{y}_0) = 0$ for all $\vec{x}_0$ and $\vec{y}_0$, $V_t^{DP}(0, \vec{y}_t) = 0$ for all *t* and $\vec{y}_t$ and $V_t^{DP}(\vec{x}_t, 0) = 0$ for all *t* and x_t. However, due to the high dimensionality of the dynamic programming formulation the CDLP and SDCP heuristics, introduced in subsection 5.3.3, are used to approximate the value function. The **choice-based LP** formulation for the network allocation of charging bundles is the following:

$$V^{CDLP} = max \sum_{S \subseteq J} \lambda R(S) \tau(S) \tag{6.14}$$

$$s.t. \quad \sum_{S \subseteq J} \lambda \vec{Q}^x(S) \tau(S) \leq \vec{x}_T \tag{6.15}$$

$$\sum_{S \subseteq J} \lambda \vec{Q}^y(S) \tau(S) \leq \vec{y}_T \tag{6.16}$$

$$\sum_{S \subseteq J} \tau(S) \leq T \tag{6.17}$$

$$\tau(S) \geq 0, \quad \forall\, S \subseteq J \tag{6.18}$$

where the decision variable $\boldsymbol{\tau(S)}$ can be interpreted as the number of steps during which set S should be offered in order to maximise revenue. This approach gives a deterministic and aggregated solution to the optimal sequence of offer sets through the optimisation horizon. Since the large number of non-empty subsets (2^n) makes the problem computationally expensive, typically a column generation algorithm[78] is employed to overcome this issue. However, column generation becomes NP-complete for overlapping consideration sets even for the MNL model (Bront et al., 2009). On the contrary, the *SDCP* formulation that was mentioned in 5.3.3 reduces the computational time significantly and is suitable for applications with more generalised discrete choice models. The SDCP specification for the optimal allocation of charging services is presented below:

$$V^{SDCP} = max \sum_{\ell} \lambda_\ell \sum_{S_\ell \in C_\ell} R_\ell(S_\ell) \tau_\ell\,(S_\ell) \tag{6.19}$$

$$s.t. \quad \sum_{\ell} \lambda_\ell \sum_{S_\ell \in C_\ell} \vec{Q}^x{}_\ell(S_\ell) \tau_\ell\,(S_\ell) \leq \vec{x}_T \tag{6.20}$$

[78] The algorithm starts with a small number of columns (subsets) for which the LP problem is solved. Then if there is any other column that has a positive reduced cost compared to the limited problem, it is added to the initial set and the LP is re-solved. For overlapping segments, this is a fractional programming problem, which is known to be NP-hard. The solution can be approximated with a greedy heuristic that starts from an empty set and sequentially adds products according to their marginal contribution to the revenue.

$$\sum_{\ell} \lambda_\ell \sum_{S_\ell \in C_\ell} \vec{Q}^y{}_\ell(S_\ell)\tau_\ell(S_\ell) \leq \vec{y}_T \tag{6.21}$$

$$\sum_{S_\ell \in C_\ell} \tau_\ell(S_\ell) \leq \lambda_\ell T, \quad for\ all\ \ell \tag{6.22}$$

$$\tau_\ell(S_\ell) \geq 0, \qquad \forall\, S_\ell \subseteq C_\ell \tag{6.23}$$

For non-overlapping segments, SDCP coincides with CDLP. For overlapping segments it is a relaxation of CDLP, hence providing a looser upper bound on the stochastic formulation. Therefore, its drawback is some increased sub-optimality in the approximation of the dynamic program. It is a rational assumption that the number of charging bundles in the consideration set of a segment ℓ is small because a single customer wouldn't process too many options to make a decision. Therefore, breaking the problem to segment-based variables $\tau_\ell(S_\ell)$ makes it more tractable and it can be solved by simple enumeration without the need of a column generation algorithm.

Talluri et al. (2011) have tightened the bounds of the above problem using the Randomised Concave Programming (RCP) method, which is similar to the RLP, mentioned in subsection 5.3.2.

After solving the static approximation problem to find the optimal number of time-steps for each subset, most of the researchers develop a simulation process to obtain a dynamic control policy. For the majority of CDLP applications, they decompose the network to single-resource problems based on the dual solutions of the original problem (Bront et al., 2009; Liu and van Ryzin, 2008; Meissner et al., 2013). Talluri et al. (2011) assume that the variables $\tau(S)$ are parameters of a Bernoulli random variable for the set S. Likewise, in their SDCP application the randomisation is taking place for each segment separately using the variables $\tau_\ell(S_\ell)$ and the final set is the union of the offer sets S_ℓ.

6.6.2 Results

In order to assess the benefits of the revenue management model compared to the FCFS simulation, the 25% EVs – 0% headroom scenario is selected because it has been extensively analysed in section 6.4. In this case, instead of NLP and LP scenarios, only one pricing strategy exists: this of the optimised price vector from the previous section. The final results are presented in Table 6.3.

Table 6.3: Choice-based network RM results for the two regions (25% EVs and 0% capacity headroom scenario)

Parking location	**Westfield**				**Canary Wharf**			
Hour Slots	09:00-10:00	10:00-11:00	11:00-12:00	12:00-13:00	09:00-10:00	10:00-11:00	11:00-12:00	12:00-13:00
Without V2G								
Parking Load Factor	47%/53%	7%/13%	0%/0%	10%/13%	37%/41%	7%/7%	0%/0%	7%/7%
Marginal Revenue from an additional kW (£)	0.42	0.79	1.61	0.63	0.42	0.71	1.48	0.43
Imbalance Costs (£)	0	0	0	0	0	0	0	0
Net Revenue (£)	1453				1426			
With V2G								
Parking Load Factor	7%/12%	5%/12%	57%/34%	18%/2%	3%/30%	13%/27%	14%/10%	100%/5%
Marginal Revenue from an additional kW (£)	0	0.19	0.32	0	0	0	0.15	0.1
Imbalance Costs (£)	118	0	0	44	145	28	0	0
Net Revenue (£)	1393				799			

For the scenarios without V2G, the most obvious difference compared to the respective uncontrolled scenarios is that there is no spare capacity after the allocation of the requested charging events. For this reason, the imbalance costs are zero during the whole time-window and, as a result, the net revenues are equal to the revenues generated from selling the charging bundles. Therefore, the control algorithm optimally allocates all the available power and increases the net revenue for both regions.

The parking load factor is similar to the FCFS simulation apart from the hour slot with the higher power availability (i.e. 09:00am-10:00am) where there is a significant increase in the number of utilised charging posts. As is it was expected, the marginal revenue from adding an extra unit of power capacity (i.e. the dual values of the optimisation constraints) is higher for the time period where the capacity headroom is zero.

On the other hand, when V2G services are offered, the opportunity to get reimbursed for selling electricity back to the grid leads to an increase of the spare capacity and of the imbalance costs that are associated with the respective hour slots. However, the net revenue is significantly higher than for the uncontrolled scenarios.

In this case, parking load factors have a distinctive difference from the FCFS results. In Westfield, a great share of the individuals that were previously plugging-in their vehicles off-peak, now are shifted to the peak hour slot (11:00 am – 12:00 pm) since this opportunity was created from the V2G-provided energy. Likewise, in Canary Wharf, this shift is observed for the last hour slot where one parking facility reaches full capacity. These movements reflect the time of day that customers with low energy demands arrive and hence they consider to sell electricity to the CSP. At the same time, previously non-allocated vehicles or drivers who preferred these time periods but have chosen the next best available option were now shifted to these slots.

It is observed in Table 6.3 that the net revenue of the V2G scenario is reduced for both areas compared to the scenario without V2G. In order to explain this reduction, the optimal price for the average charging bundle has been calculated based on the values of Table 6.2. For Westfield, when V2G scenario is applied the average product price is reduced from £4.02 to £3.72. Likewise, for Canary Wharf, it is reduced from £2.89 to £2.22. This can partially justify the decrease in net revenue. The relative differences between the two areas are not proportionate due to the dissimilarities in the demand characteristics.

Finally, the marginal revenues from adding an extra unit of power capacity are quite low compared to the scenarios without V2G. In particular, the marginal revenue is equal to zero for two hour-slots in both areas. Irrespective to the imbalance costs that are incurred to the CSP, this means that V2G implementation partially satisfied the energy needs of the users and hence it reduced the demand for additional generation capacity.

A comparative analysis was undertaken to highlight the differences in energy requirements for varying scenarios of EV penetration rate, headroom capacity and V2G availability. Figure 6.25 shows that the energy levels increase for higher EV rates and increased capacity headroom. In cases where charging demand is largely satisfied, the energy requirements remain rather stable when we move from 10% to 20% capacity headroom. It is important to note here that there is a significant reduction when V2G services are provided. This observation supports the point made above, regarding the reduced needs for generation capacity.

In order to demonstrate some of the potential applications of the developed model, two sets of sensitivity analyses have been performed (Latinopoulos et al., 2014). The first refers to the sensitivity of the revenue outcome to marginal changes in the two capacity dimensions, assuming that all other parameters remain fixed and that the customer arrival distribution is known beforehand by the operator. The performance of this sensitivity analysis for the Westfield area (with and without V2G services) is illustrated in Table 6.4. The conclusions drawn from this sensitivity analysis are quite similar for the Canary Wharf area, thus, these results are not presented here.

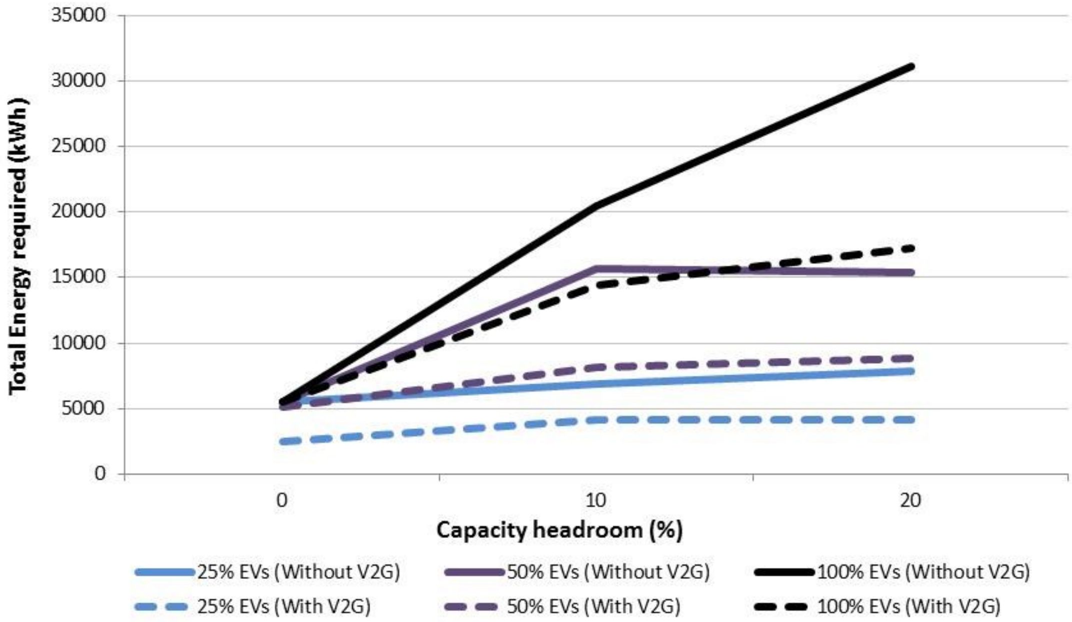

Figure 6.25: Energy requirements for all possible scenarios of the RM application

Since the initial assumption for charging posts exceeds demand in the 25% EV-penetration scenario, only scenarios with lower charging post capacities are analysed. Charging post capacity starts having an actual effect on revenue after a 60% reduction, so the CSP could operate with 250 charging posts for each facility (instead of 625) without significant revenue impacts. On the other hand, the minimal requirement for the substation is that the capacity is equal to peak electricity load, i.e. the headroom capacity is zero. Therefore, only scenarios with increased power availability are analysed.

The fifth column of Table 6.4 shows the charging post load factor, which is the percentage of charging posts that are occupied, for the whole network, and for parking facilities 1 and 2 separately. Similarly, the sixth column shows the power load factor, which is the percentage of the kW provided by the operator that is reserved by the EV drivers. All load factors are inversely related to the respective capacity.

As it was expected both capacities are positively correlated with revenue. However, for the given demand levels this is not a linear relationship because power capacity is fully allocated much faster than charging post units. The base case scenario is the one that was used for the comparison with the FCFS simulation. Then, charging post capacity and increased headroom capacities are evaluated sequentially, after the application of a scale factor.

Table 6.4: Sensitivity analysis to changing capacities in the two parking facilities

Charging post capacity scale	Capacity headroom	Revenue (in £/day)	Revenue loss/gain (in %)	Charging post Load Factor [Total, Parking facility 1, Parking facility 2]	Power Load Factor [Total, Parking facility 1, Parking facility 2, Off-peak, Peak]
Without V2G					
1.0	**0%**	1453	0	[0.18, 0.16, 0.20]	[**1.00,1.00,1.00,1.00,1.00**]
0.6	**0%**	1453	0	[0.30, 0.26, 0.33]	[**1.00,1.00,1.00,1.00,1.00**]
0.4	**0%**	1426	-2%	[0.38, 0.37, 0.39]	[**1.00,1.00,1.00,1.00,1.00**]
0.2	**0%**	1184	-19%	[0.58, 0.58, 0.58]	[0.84, 0.90,0.78,0.82,**1.00**]
1.0	**10%**	2169	+49%	[0.23, 0.26, 0.19]	[0.19,0.21,0.17,0.04,0.42]
1.0	**20%**	953	-34%	[0.23, 0.28, 0.18]	[0.11,0.13,0.09,0.03,0.22]
With V2G					
1.0	**0%**	1393	0	[0.18, 0.22, 0.15]	[0.90,**1.00**,0.72,0.78,**1.00**]
0.6	**0%**	1182	-15%	[0.22, 0.22, 0.22]	[0.86,0.94,0.76,0.82,**1.00**]
0.4	**0%**	1182	-15%	[0.33, 0.33, 0.33]	[0.86,0.94,0.76,0.82,**1.00**]
0.2	**0%**	1118	-20%	[0.58, 0.58, 0.58]	[0.82,0.88,0.76,0.802,**1.00**]
1.0	**10%**	592	-58%	[0.12, 0.13, 0.11]	[0.22,0.22,0.22,0.04,0.44]
1.0	**20%**	-636	-191%	[0.12, 0.13, 0.11]	[0.12,0.14,0.10,0.04,0.22]

The weighted average of the charging speed from the discrete demand distribution is approximately 4kW. Therefore, a marginal change in capacity of one charging post would be similar to a marginal change of 4kW in the charging availability. Moving from 100% to 20% charging post capacity, 1000 individual charging units are removed (or 4000 charging opportunities if each hour slot is considered). On the other hand, increasing the headroom capacity from 0% to 10% an amount of 20.5MW is added for the whole network, that could be used to serve approximately 5,125 vehicles). As a result, the ratio of revenue gains/losses between power and charging post capacity should be 1.28, if the two dimensions had the same effect on the sensitivity analysis. However, it is observed that this ratio is 2.66 and subsequently, power dimension is associated with proportionally higher marginal revenues compared to the physical dimension.

For the scenario without V2G, it is observed that after a 10% increase of headroom capacity, the net revenue for the CSP decreases instead of increasing. This is due to the remaining power and the associated imbalance costs and it is also visible in the power load factors that drop significantly. Here there are two options for the CSP: a) to run a similar sensitivity analysis in order to find the optimal headroom capacity, i.e. the point after which net revenue starts decreasing or b) to use the power load factors as indicators of how much energy is required for each time period and parking location, and negotiate an approximate energy amount with the DSO instead of pre-empting all the available spare capacity.

When V2G bundles are included in the choice set, the net revenue is reduced because of the proportion of the drivers that have to be paid back for offering electricity to the grid. Nevertheless, in contrast to the scenario without V2G, the power capacity is augmented by the amount of discharging, and hence, it is not fully consumed. In this case, obtaining robust predictions about the share of EV drivers that are willing to participate in V2G markets, the CSP could negotiate a lower energy amount with the DSO and cover the additional needs from the plugged-in vehicles.

The above are visualised in Figure 6.26. The top two subplots show how net revenue fluctuates for changing capacities while the bottom subplots show the same effect for parking load factor.

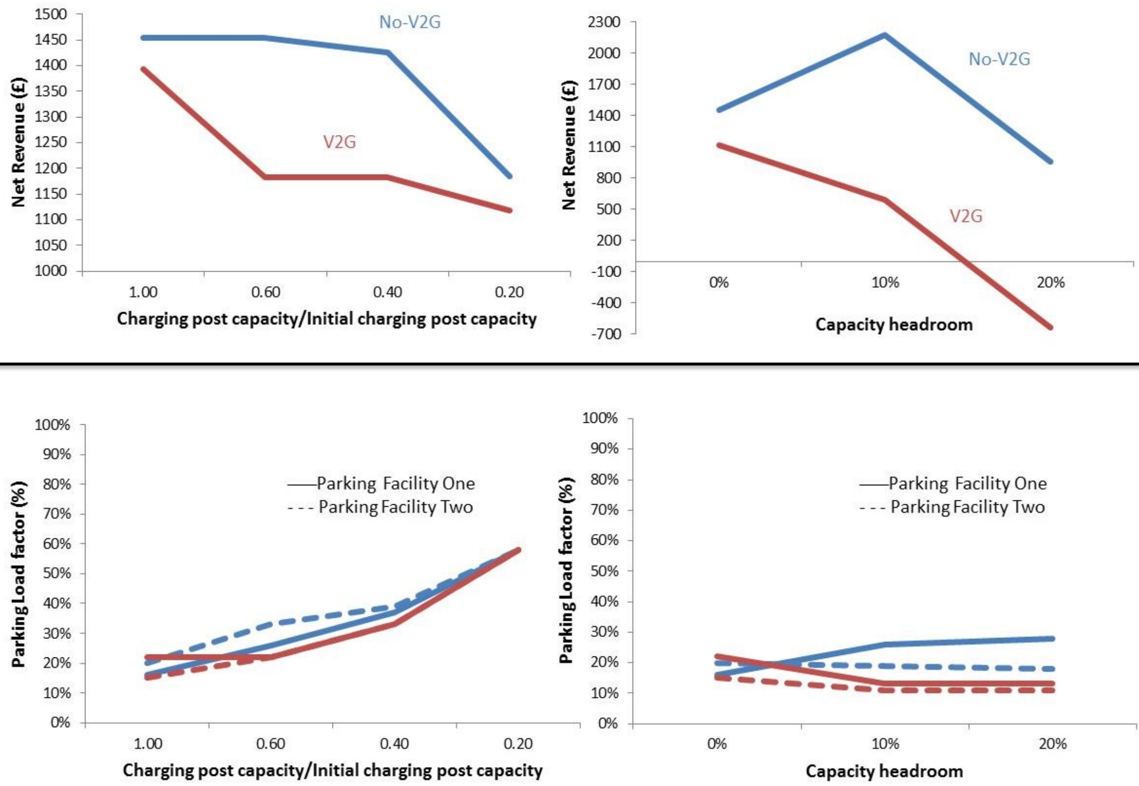

Figure 6.26: Graphical presentation of sensitivity analysis to the two capacity dimensions

Another interesting aspect of the problem lies in the demand side and the revenue performance under uncertainty for the characteristics of the market segments. For this sensitivity analysis, it is examined how choice parameter variability propagates in the model output when capacity is fixed both in the physical and in the power dimension (Table 6.5). In particular, the parameters that have been selected for sensitivity analysis are:

- The alternative specific constant, which defines the proportion of EV drivers that "opt-out" and do not charge their vehicle at all. This parameter was not estimated for reasons that were explained in Chapter 4, and thus, an initial value was assumed for this analysis, which guaranteed that only a small proportion of drivers were not buying any of the charging bundles available. At this point, the sensitivity analysis shows the modification in the RM performance from different ASC values.
- The parameter of the energy that is delivered to the vehicle. The original parameter was adopted from Daina (2014), as a proxy to the sensitivity to the final SOC of the vehicle. Since this is a strong assumption, the sensitivity analysis below shows how the uncertainty associated with this estimate affects the RM system. It is interesting here, to see the effects on the V2G-based scenario where the energy parameter of a discharging bundle has a negative effect on the utility of the individual.
- The sensitivity to price for the two latent classes. Contrary to the two parameters above, this sensitivity has been estimated as part of the work reported in this thesis. Nevertheless, there is a certain degree of uncertainty regarding the tariff structure of the joint parking/charging bundles as well as for the future changes in electricity prices. As a result, it was considered essential to examine the effect of this uncertainty with varying price sensitivities.

The results of Table 6.5 show that the ASC parameter has a great impact on revenue performance. This indicates the necessity to understand the "no-purchase" option in the estimation of charging preferences and to properly capture the market share that will opt-out without selecting any of the CSP's services.

The energy parameter has a relatively weak effect on revenue for the scenario without V2G. In particular, when it is doubled the increase in revenue is 1% whereas when it is quadrupled the respective increase is 2%. When V2G services are provided, the results are less intuitive due to the conflicting effects of charging and discharging services. Therefore, it can be observed that there is a significant 10% reduction in revenue when the parameter is doubled. Nevertheless, if the sensitivity increases even more this reduction in revenue becomes 3%. A potential explanation is that some drivers will not participate in V2G services, and subsequently, they will not provide the power that would generate revenue from other customers.

Table 6.5: Sensitivity analysis to changing choice parameters

ASC	Energy	Price (PC/TC)[1]	Revenue (in £/day)	Revenue loss/gain (in %)	Charging post Load Factor [Total, Parking facility 1, Parking facility 2]	Power Load Factor [Total, Parking facility 1, Parking facility 2, Off-peak, Peak]
Without V2G						
5.0	**0.094**	**-1.43/-0.769**	1453	0	[0.18, 0.16, 0.20]	**[1.00,1.00,1.00,1.00,1.00]**
3.0	**0.094**	**-1.43/-0.769**	1388	-4%	[0.18, 0.16, 0.20]	**[1.00,1.00,1.00,1.00,1.00]**
1.0	**0.094**	**-1.43/-0.769**	446	-69%	[0.08, 0.10, 0.07]	**[1.00,1.00,1.00,1.00,1.00]**
5.0	**0.188**	**-1.43/-0.769**	1474	+1%	[0.16, 0.16, 0.16]	**[1.00,1.00,1.00,1.00,1.00]**
5.0	**0.376**	**-1.43/-0.769**	1480	+2%	[0.16, 0.16, 0.16]	**[1.00,1.00,1.00,1.00,1.00]**
5.0	**0.094**	**-2.86/-1.538**	1376	-5%	[0.18, 0.16, 0.21]	**[1.00,1.00,1.00,1.00,1.00]**
5.0	**0.094**	**-0.72/-0.384**	1475	+2%	[0.16, 0.16, 0.16]	**[1.00,1.00,1.00,1.00,1.00]**
With V2G						
5.0	**0.094**	**-1.43/-0.769**	1393	0	[0.18, 0.22, 0.15]	[0.90,1.00,0.72,0.78,**1.00**]
3.0	**0.094**	**-1.43/-0.769**	809	-42%	[0.11, 0.12, 0.09]	[0.64,0.77,0.51,0.60,**1.00**]
1.0	**0.094**	**-1.43/-0.769**	231	-83%	[0.06, 0.07, 0.05]	[0.31,0.38,0.25,0.26,0.85]
5.0	**0.188**	**-1.43/-0.769**	1255	-10%	[0.13, 0.11, 0.15]	[0.86,0.73,**1.00**,0.85,**1.00**]
5.0	**0.376**	**-1.43/-0.769**	1352	-3%	[0.14, 0.13, 0.14]	[0.92,0.83,**1.00**,0.91,**1.00**]
5.0	**0.094**	**-2.86/-1.538**	737	-47%	[0.11, 0.12, 0.10]	[0.64,0.79,0.50,0.61,**1.00**]
5.0	**0.094**	**-0.72/-0.384**	1298	-7%	[0.14, 0.13, 0.14]	[0.89,0.83,0.95,0.88,**1.00**]

[1] PC/TC = Price-Conscious/Time-Conscious

The results of the sensitivity analysis for price are similar. If there are no V2G services, an increased sensitivity to price has negative effects on revenue while a decreased sensitivity to price has positive effects on revenue. On the other hand, V2G availability complicates the outcomes. For the same increase in sensitivity, the reduction in revenue is 47% instead of 5%. However, the revenue is reduced by 7% even for decreased sensitivity. It is speculated that the explanation is similar to the one described above.

Finally, it was examined if the revenue outcome is sensitive to the proportion of price-conscious and time-conscious users in the population. In Figure 6.27 it can be seen that for different segment mixtures the net revenue for the scenario without V2G remains quite stable. On the contrary, for an increasing ratio of price-conscious/time-conscious customers the net revenue for the scenario with V2G services steadily increases. This can be attributed to the fact that users who are more sensitive to price will sell electricity back to the grid in order to get reimbursed, and the additional power capacity will enable other customers to charge their vehicles during peak hours.

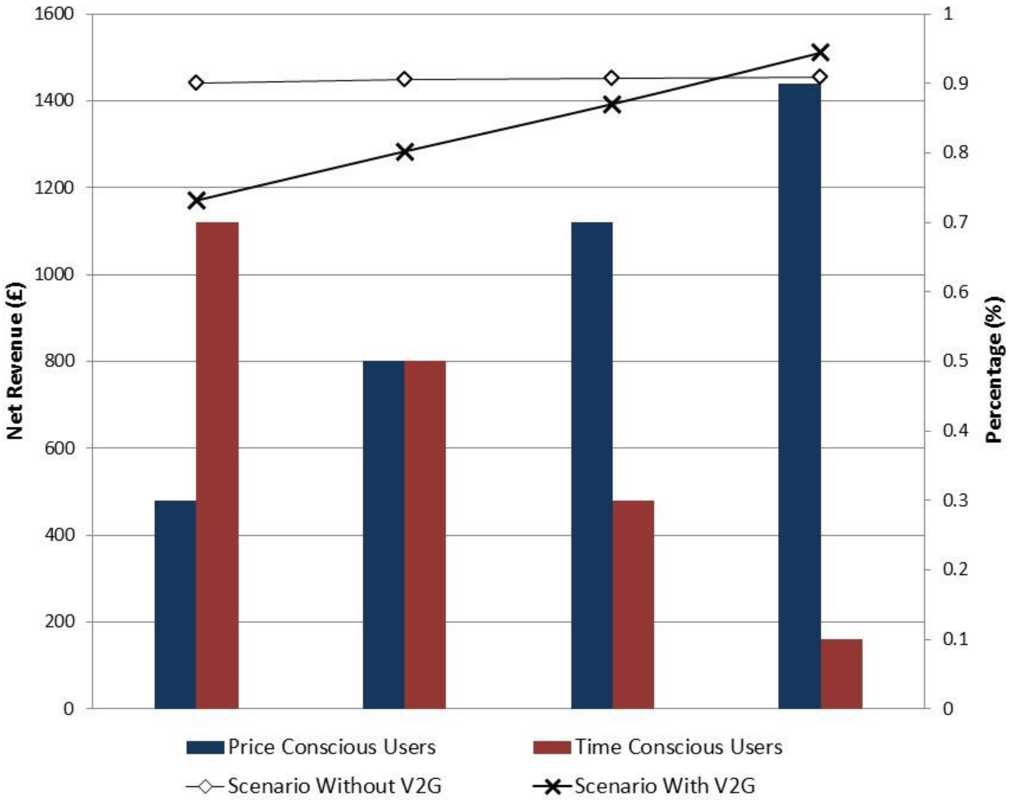

Figure 6.27: Sensitivity analysis for segmentation mix

6.7 Extensions of conceptual framework for strategic customers

In this section, the theoretical framework for incorporating strategic behaviour in the revenue management problem is presented. Empirical analysis with the extended framework was out of the scope of this thesis, however, it is considered a fruitful area for future research. The parameters estimated in Chapter 4 for the "buy-or-wait" decision under dynamic pricing can be used to differentiate between myopic and strategic customers, but ideally, they should be complemented by revealed preferences in a booking environment.

In the recent literature on revenue management, there has been a significant amount of studies that examine the inter-temporal substitution by customers and its effect for the operators. The first step in understanding when people prefer to buy a particular product is to model their response to dynamic pricing methods. Subsection 2.3.9 and section 4.3 provide some insights towards this direction, covering energy consumption and RM applications respectively. The following step is to study how operators should modify their optimal control policies in order to address the presence of strategic customers. This section demonstrates some representative methods in this research area.

6.7.1 Dynamic pricing under strategic behaviour

Talluri and van Ryzin (2004a) argue that the application of revenue management with myopic behaviour assumptions may be acceptable for markets with spontaneous customers (e.g. low-price products like charging price in this study) and for situations where customers do not have the appropriate time and information to strategize their decision-making. On the other hand, explicitly treating strategic behaviour becomes valuable for more expensive products and for an increasing availability of information. In this case, failing to incorporate strategic behaviour could possible result in significant reductions of the revenue from dynamic pricing.

In the case of EV recharging the price of the service might be relatively low for single decisions, but considering that it is a continuous process, the cumulative cost on a monthly basis could be significantly affected. Thus, given that there is adequate information for future prices, it is quite likely that some drivers will delay their reservation in the expectation of a cheaper charging bundle.

Typically, optimal pricing in the presence of strategic customers is modelled with game theoretical approaches. The most appropriate game framework is this where the seller acts as a Stackelberg leader announcing the price and the customers are the followers who modify their purchasing behaviour (Levin et al., 2010). For example, Aviv and Pazgal (2008) suggest subgame-perfect Nash equilibria between the seller and strategic individuals, evaluated for fixed discounts and inventory-dependent discounts. Moreover, the majority of the studies in this area simplify the general multi-period dynamic program down to a two-period problem (Liu and van Ryzin, 2008b; Zhang and Cooper, 2008; Cachon and Swinney, 2009).

For the two-period problem, if the supplier follows a single markdown policy, i.e. prices monotonically decrease in time (e.g. fashion retailers) then the price for the second period p_2 is always lower than the price for the first period p_1. If u(.) is the utility function for an individual, v is his valuation for the product of interest and q is the probability that the product will be available in the second period, then the individual will buy the product in period 1, only if $u(v - p_1) \geq qu(v - p_2)$ and his valuation is higher than the price in period 1, i.e. $v - p_1 \geq 0$. It is expected that customers with high valuations will buy at period 1 because their utility would significantly decrease in the case of non-availability in period 2. This choice process is graphically presented in Figure 6.28.

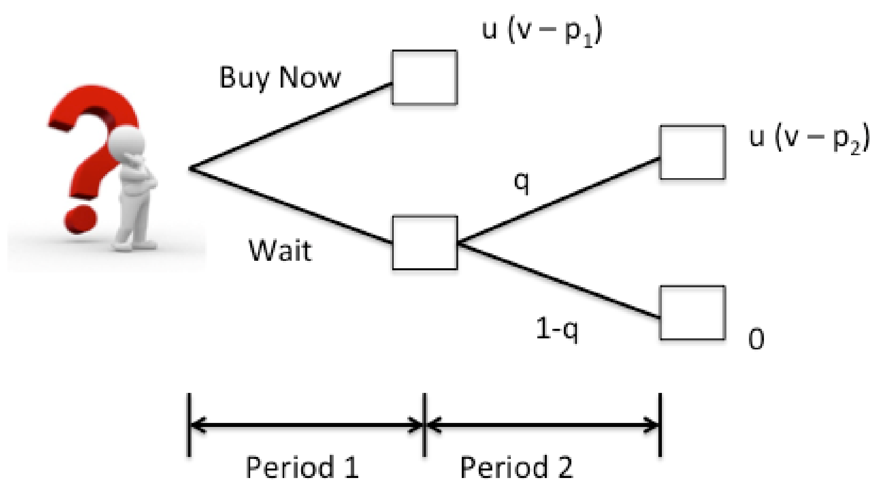

Figure 6.28: Schematic representation of "buy now or wait" choice for the two-period problem

Levin et al. (2010) relax the assumption of decreasing price paths since there are several service industries (e.g. airlines, hotels) where markdown policies are not applicable. This relaxation allows a better interpretation of the dynamics of the interaction between the seller and the customers. Their stochastic game is extremely difficult to analyse in the presence of imperfect information. Subsequently, they transform the problem into a perfect information game, a simplification that is common for similar studies. Under this assumption, customers can rationally predict the behaviour of others.

The findings of this study also suggest that if the operator uses the strategic equilibrium pricing policy that is defined from the stochastic game, the loss of revenues due to the existence of strategic behaviour is significantly lower than in the case of completely ignoring this behaviour. At the same direction, Aviv and Pazgal (2008) found that the loss by ignoring strategic behaviour could reach to 20% while in Besanko and Winston (1990) this loss goes up to 60%.

The findings in Su (2007) support our two-stage estimation in Chapter 4 because their results suggest that the optimal pricing strategy is influenced by customer heterogeneity both in product valuations and in waiting costs. The modelling approach that is presented in this section is similar to this of Baucells et al. (2014) with the main difference that charging prices can move in both directions and the operator does not apply a markdown policy.

6.7.2 Game theory for charging coordination

The game involves one retailer (the CSP) and a continuum of EV drivers with a total mass of $\lambda > 0$. Each driver has a certain valuation u and the cumulative distribution of these valuations

F(u) is continuous with support $[0, \bar{u}]$, $\bar{u} > p_1$. The CSP has an initial availability of Q charging posts. At the beginning of the first period, the examined charging bundle is priced at p_1 and the provider's management problem is to choose the discount/surcharge factor $d \in [-1,1]$ that should be applied for period 2.

An EV driver arriving at the beginning of period 1 observes the set (Q, p_1,d) and has three options: opt-out without buying, buy now at price p_1 or wait until period 2 and buy at price $p_2 = p_1$(1-d), although, taking the risk of charging post non-availability[79]. Based on a Nash game, all EV drivers act simultaneously without observing each other's decisions. The mass of consumers that buy now is denoted by λ_1 whereas the mass of consumers that wait is denoted by λ_2. If $\lambda_1 \leq Q$ then the "buy now" drivers pay p_1 while for $\lambda_1 > Q$ some drivers are randomly allocated to the available charging posts. Likewise, the probability of obtaining a charging bundle in period 2 is equal to the remaining charging posts divided by the number of drivers that choose to wait. Mathematically, the probabilities of obtaining a charging post in periods 1 and 2 can be expressed as follows:

$$q_1 = \min\left(\frac{Q}{\lambda_1}, 1\right) \tag{6.24}$$

$$q_2 = \min\left(\frac{\max(Q - \lambda_1, 0)}{\lambda_2}, 1\right) \tag{6.25}$$

for $\lambda_1 > 0$ and $\lambda_2 > 0$. Clearance is modelled as an instantaneous event. Finally, drivers are assumed to have perfect knowledge of the probability of charging post availability.

If V is the payoff function for choosing one of the alternative options then:

$$V_{opt-out} = 0 \tag{6.26}$$

$$V_{buy-now} = f(p_1) \tag{6.27}$$

$$V_{wait} = g(p_1, d, q, t) \tag{6.28}$$

where f and g are functions and t is the time elapsed until the second period. For long waiting times, the driver might be negatively affected based on a waiting penalty factor. As a result,

[79] As it was explained in Chapter 3, the probability of charging post availability was not used in the booking game because it would create an additional dimension of uncertainty, increasing the level of complexity for the participants. Since this section is a theoretical demonstration of the price optimisation problem for strategic customers, the lack of this parameter does not affect our analysis. However, for future research it is essential to take into account this additional factor either through revealed preferences or (more realistically) through appropriate laboratory experiments.

the payoff function for waiting might deviate from Expected Utility theory to Discounted Expected Utility theory in order to take into account the implicit disutility from the waiting action per se.

The prospect theoretical approach for the asymmetric effect of gains and losses that was presented in Chapter 4 could be implemented in the following way: the discount/surcharge factor *d* instead of a definite value is expressed as a prospect with various different outcomes, the probability distribution of which is known by the EV drivers and its expected value is E(*d*).

The payoff for the CSP is the expected revenue, which is calculated as follows:

$$R = p_1 \min\{\lambda_1, Q\} + p_1(1 - E(d))\min\{\lambda_2, \max(Q - \lambda_1, 0)\} \tag{6.29}$$

Since the structure of the selling mechanism is that of a Stackelberg game, first, the reaction of the drivers (followers) is examined and then the problem of the CSP (leader) is considered.

For markdown policies (i.e. d>0) if the price of the first period is normalised so that $p_1 \in [0,1]$ then it is possible to characterise the best response of the drivers with a threshold $H \in [p, 1]$. Specifically, if:

- $0 \leq u \leq p_1\big(1 - E(d)\big)$, then buying is never preferable for the individual and opting out is a dominant strategy
- $p_1(1 - E(d)) \leq u < p_1$, then "buying now" is never profitable for the individual and waiting is a dominant strategy
- $p_1 \leq u < 1$ then the driver has to form some expectation about the probabilities to find a charging post in period 1 and in period 2. Payoff functions for waiting and buying are linear and they have one intersection at H, therefore, the driver will wait for $p_1(1 - E(d)) \leq u \leq H$ and will buy now for $H < u \leq 1$.

If all drivers use the same threshold *H*, the best response is B(H) and the equilibrium condition is B(H)=H, then, it is proved by Baucells et al. (2014) that there is at least one fixed point H* for which B(H*)=H* and hence a symmetric equilibrium in pure strategies exists. If the supply from the CSP is not close to abundant, then it can be also proved that there are multiple equilibria and the problem becomes a game of coordination. In this case, the equilibrium with the highest H^* is Pareto dominant and thus it is selected.

Having defined the equilibrium consumer behaviour, the goal of the CSP is to identify the selling arrangement that will maximise:

$$R(H^*) = p_1 \min\{\lambda\bar{F}(H^*), Q\} + p_1(1 - E(d))\min\{\lambda(F(H^*) - F(p_1(1 - E(d))), \max(Q - \lambda\bar{F}(H^*), 0)\} \tag{6.30}$$

where $\bar{F} = 1 - F$.

6.7.3 Conceptual framework with strategic behaviour

The conceptual framework for the RM application of this thesis that was presented in section 6.2 can be extended to take into account customer strategic behaviour. This extension is illustrated in Figure 6.29.

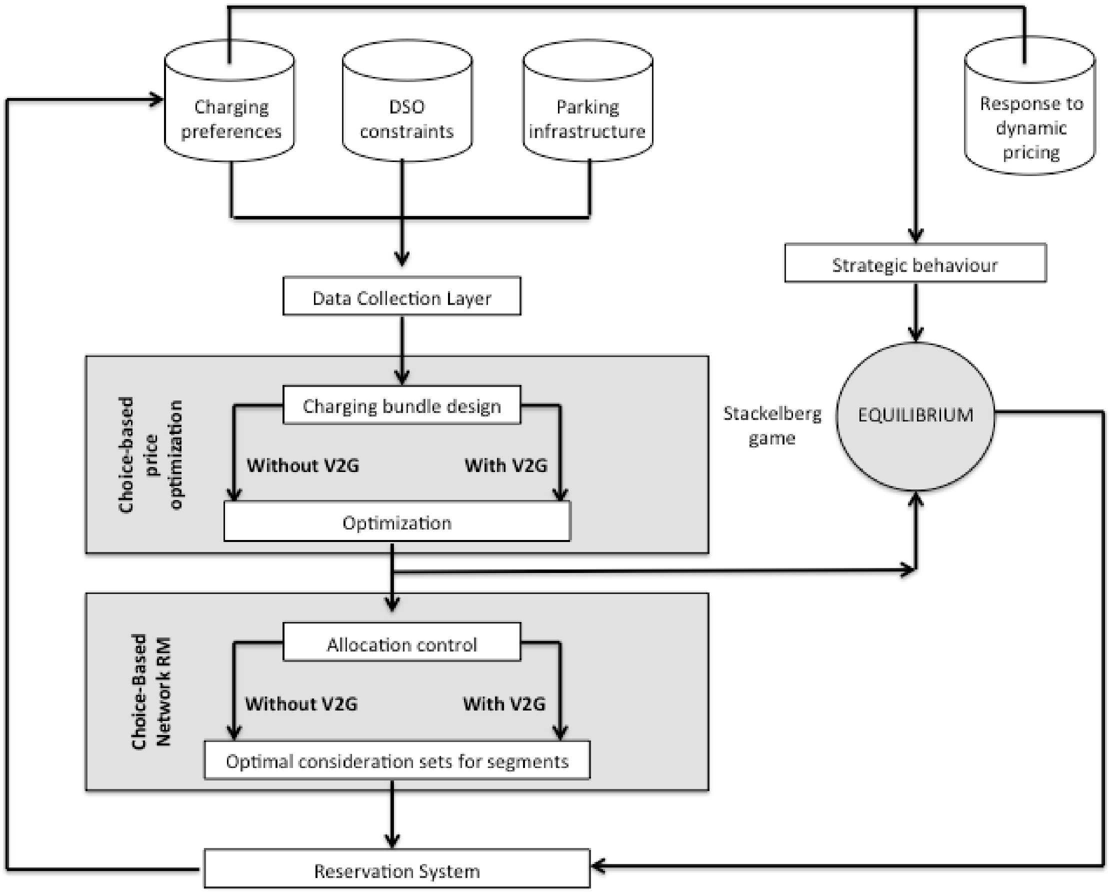

Figure 6.29: Conceptual framework of RM for Charging Service Provider when accounting for strategic behaviour

Some of the drawbacks of the suggested methodology are:

- The two-period simplification does not allow more sophisticated strategic processes (e.g. the EV driver observes some price modifications to form an opinion about the moving patterns before booking a charging event).

- The stochastic game is applied for each charging bundle separately without taking into account their competitive characteristics
- For existing energy prices, EV drivers are less likely to delay their purchases for the uncertain prospect of finding a better deal (A significant proportion of the respondents in the booking game demonstrated a risk-prone behaviour, probably because they were not dealing with real payoffs. Nevertheless, individuals in revealed preference contexts are more likely to be risk-averse).

Regardless its drawbacks, it should be considered for future applications of dynamic pricing, especially for situations where intermediate information providers give recommendations for the time of reservation like it is the case with airline tickets today. Response to dynamic pricing has great implications for a charging service provider, both in terms of the generated revenue and the ability to make robust predictions and satisfy power network constraints.

6.8 Recommendations for practical implementation of the suggested framework by CSPs

The first step for the implementation of the RM framework is to perform a *segmentation* of EV customers. As it was described in Chapter 4, this can be achieved with a latent class model, and if qualitative data for the customers is available or easy to collect, with a hybrid latent class model. Based on our estimation, some of the most important attributes for classifying the users are: employment status, marital status and attitude towards pre-planning travel activities. These customer-specific attributes constitute the *segmentation basis* for the CSP. Some additional attributes to enrich the segmentation strategy, assuming future availability of revealed preference data, are:

- Time of purchase (The estimates of the risky choice model in Chapter 4 suggest that EV drivers with higher elasticity to price will reserve a charging post earlier than time-sensitive EV drivers)
- Cancellation penalties (individuals who are more credible when making reservations should be rewarded compared to those that tend to make cancellations)
- Spent amount (e.g. in leisure or shopping locations CSPs could tailor the charging services based on the amount spent by the individual on related activities like food or beverages)

- Loyalty (Regular users of the contracted parking facilities could be rewarded with discount cards or "frequent-charger" cards in order to be separated from occasional users)

Segmentation should then be evaluated according to the following criteria (Talluri and van Ryzin, 2004a):

- Identifiability: Price-conscious and time-conscious users have to be identified either before or after the purchase.
- Substantiality: If the number of EV drivers in one of the segments is too small compared to the others, then the benefits of segmentation might not be justified by the costs.
- Reachability: The CSP has to make sure that the drivers are stimulated to self-select the targeted charging bundles.
- Stability: If the behaviour among EV driver classes changes rapidly over time it is difficult for the CSP to estimate the characteristics of each segment.
- Responsiveness: If customers of the same class (e.g. price-conscious) do not demonstrate homogeneity in their response to the CSP's pricing tools, the effectiveness of the segmentation method is arguable.
- Actionability: Last but not least, the CSP needs to base charging bundle design and marketing decisions on the segmentation levels. Such customizations (e.g. segment-based or personalised pricing) should be feasible and legally permitted in the general area of operation (i.e. power markets).

The second step after segmentation is the proper *design of charging bundles* that will be targeted to each customer class. The underlying concept in product design is to charge higher tariffs to the drivers that have higher willingness to pay. The set of charging bundles that were presented in this chapter was indicative and it could be extended to capture a wider range of discrete charging rates or periods of operation.

The computational intensity both for forecasting and for optimisation can be immense, thus, hardware and software requirements are increased. Simultaneously, human intervention at the automated process is an indispensable part of revenue management. Analysts should be able to interact with the control system in the case of unusual market conditions (e.g. exogenous factors that increase charging demand) or system errors. Looking at the paradigm of automated trading for financial markets, it is also necessary to take the adequate measures in designing, testing and supervising the system in order to avoid disruptive events (e.g. caused by malfunctioning algorithms).

The developed methodological framework can be characterised as the *revenue-opportunity assessment,* which is required during the pre-implementation stage to evaluate the potential benefits for the CSP. Likewise, after implementation, the CSP needs to validate the pre-assessed benefits with an analysis that is called *revenue-benefits measurement.* Apart from validation, this stage can be seen as an additional opportunity for improvement by identifying weak points and modifying the RM system in the most appropriate way.

A significant parameter that the CSP has to take into account is the reaction of the customers and their acceptability towards dynamic pricing. This acceptability relies on customers' perception about the reason for price differences. Therefore, looking at the presented framework, the CSP should highlight the idea of "charging rate discounts", i.e. drivers who consume less power-intensive bundles are awarded for putting less strain on the distribution network.

In addition, the operator should quantify the impact of input parameters on the performance of the system and mitigate the associated errors. For example, the base load curves for the undertaken analysis were based on some simplifications that were described in subsection 6.3.1. For implementation, the CSP could consider applying a more sophisticated approach to model energy consumption in the area of operation. The integration with proper communication systems and smart metering devices is crucial, in order to reduce uncertainties regarding exogenous electricity consumption (e.g. home appliances) or unexpected real-time charging spikes. As with any smart grid application, the efficiency of communication technologies relies on the minimisation of system latency. The consecutive requests for charging post reservations and the massive flow of information from smart meters must be analysed in real-time and communication delays could compromise the optimality of the outcomes.

Finally, no matter how well the RM system is designed, there are certainly going to be unexpected events like reservation cancellations, infrastructure malfunctions or late arrivals of EVs. The CSP needs to prepare the appropriate policies and procedures so that he is able to handle these irregular situations with the minimum possible distress for the customers. The ideal compensation for unrealized charging events would be to offer an alternative charging opportunity to EV drivers in another time-slot of the day.

6.9 Summary

The density of recharging infrastructure and the ability of the CSPs to produce attractive service bundles that would turn out-of-home recharging into an appealing solution without jeopardising the network operation is a decisive factor, both for EV adoption and the subsequent coordination of charging operations. This chapter demonstrates how driver choices are integrated with an optimisation module to create a choice-based revenue management tool. Two novel decentralised approaches for charging coordination have been suggested:

- An integrated latent class and GA optimisation framework that gives a static vector of the optimal prices for the charging bundles that the CSP provides
- A segment-based deterministic concave program that is employing MNL probabilities for each different customer segment. This method adopts the optimal prices from the previous one to give an approximate upper solution to the dynamic problem.

The simulation experiments were carried out with SOCSim, a micro-simulation framework that was developed based on a synthesised network for two different regions: one where shopping/leisure is the main activity purpose (Westfield area) and one where the majority of activities are work-related (Canary Wharf). Travel and parking data were extracted with synthetic population methods while base load assumptions were made according to typical load profiles for domestic and non-domestic customers. Different scenarios for the number of EVs in the market and for the spare capacity that is available for recharging were made. Charging behaviour for the simulated vehicles was modelled according to the estimated models of Chapter 4. The various simplifications (e.g. the restriction of the operational times to a four-hour window) allowed the extraction of useful conclusions, keeping at the same time computational expense at a manageable level.

The SDCP approach is compared with a first-come-first-served uncontrolled scenario to identify the benefits of the former. One main difference between the two simulation systems is that in the FCFS system, drivers arrive at real time and they are allocated sequentially based on their preferences and the CSP's availability, whereas in SDCP they can arrive at a reservation system up to 24 hours in advance of the actual charging event.

Some interesting conclusions from this chapter are shown below:

- When locational pricing is applied for the FCFS system, the net revenue of the CSP increases substantially and at the same time, charging demand is smoothly distributed in space.
- The nonlinear optimal pricing formulation gives higher prices for bundles with higher charging rates, longer charging durations and consumption of peak period resources.
- For scenarios without V2G, the RM system allocates the spare capacity in a most efficient way and imbalance costs are minimised.
- V2G availability enables the accommodation of drivers during the peak hour whereas previously they were classified as non-allocated. Also, it reduces the marginal revenue from adding an extra unit of capacity, i.e. it covers better the energy needs and there is lower demand for additional generation capacity.
- The CSP could operate with 40% of the assumed charging-post capacity without significant revenue impacts.
- Charging quantity and price attributes have a stronger effect on revenue for the scenarios with V2G than for the scenarios without V2G. The same applies to the proportion of price-conscious and time-conscious users in the population.
- Net revenues for SDCP are higher compared to all uncontrolled scenarios and this improvement ranges between 5% and 10%. This result is in agreement with the literature in yield management for airlines where the typical improvement is in the range of 2% - 5% (Belobaba and Wilson, 1997).

The main limitations of the suggested methodological framework can be summarised in the following points:

- The forecasting capabilities of the modelling tools have yet to be validated with RP data since several exogenous factors (e.g. public acceptance of pricing out-of-home services) are not established at the moment. Ideally, this could happen with the mixed estimation of SP and RP data and by using a hold-out sample from the revealed preferences for external validation.
- The discrete space in which charging bundles are defined (categories of charging rates or starting times) helps with the creation of a tractable optimisation problem but at the same time, poses a limitation on the attribute levels that are modelled
- Likewise, the restriction of the optimisation to a 4-hour period, in order to reduce the dimensionality of the problem, might lead the analyst to miss some longer-term trade-

offs. Solving for multiple overlapping 4-hour periods over the day and averaging the results could reduce significantly this sort of error.

- The major difficulties in applying dynamic pricing for network RM settings have led to the selection of the sequential method (i.e. offline pricing and dynamic allocation) described earlier

The sensitivity analysis that followed highlighted the structural properties of the model, as well as the potential areas of interest for an operator to reduce the underlying uncertainties and increase his revenue predictability. Specifically, it was found that the availability of charging power for the operator is a substantial parameter of the optimisation problem. Nevertheless, this availability heavily depends on the average consumption of electricity by local residential, commercial and industrial users. Thus, the ability to predict this non-EV demand (e.g. smart metering) would provide the CSP with better knowledge of how to pre-allocate the incoming reservations. It is also crucial to understand how the uncertainty in choice parameters propagates into the revenue output.

One issue that has to be noted here is the complexity of the interactions between the multiple stakeholders. The framework is designed in such a way that it provides the total maximised revenue for the CSP, across all the contracted parking facilities. This optimal solution is rarely beneficial for all parking operators and infrastructure owners. For example, different pricing strategies may generate revenue for one facility at the expense of causing losses for another. The constraints of the problem can be modified accordingly, in case the objective function is targeted towards specific locations and not towards the holistic system.

As it was described in Chapter 5, parking operators or CSPs have the opportunity to participate in frequency regulation markets if they have signed V2G contracts with the EV owners. The current framework could be adapted to incorporate regulation services with the addition of mixed "charging bundles", i.e. combinations of charging and discharging intervals. However, it would be difficult to define the prices and the charging rates for these services in advance because regulation is strongly affected by real-time electricity demand.

7 CONCLUSIONS

7.1 Overview

Technology development and economic growth are currently heavily dependent on energy sources that are both environmentally and socially unsustainable. In order to change things, an energy revolution is demanded, and existing options that can be deployed in this direction are: renewable energy (e.g. solar and wind), nuclear power, energy efficiency, carbon capture and storage (CSS) and new transport technologies. A series of roadmaps have been established to cover the requirements for each of the above technologies and, hence, to achieve the targets for CO_2 emission. One of these roadmaps is addressed to new transport technologies and especially to electric and plugged-in hybrid vehicles, presenting a viable scenario for their evolution and market penetration.

Coordination is essential in order to cope with the forthcoming problems and the new needs of electro-mobility. BEV and PHEV owners will require some sort of pre-trip or en route service to overcome "range anxiety" and to take account of charging attributes and electricity price in their everyday choices. For this reason, it should be very convenient to establish a system that would allow reserving a charging-parking place for a specific time interval during out-of-home activities. This system would create a very competitive market where drivers decide between alternative parking choices based, among other parameters, on the electricity-affected parking fee.

Parking operators and charging service providers will need to distribute their customers in time and space in order to optimise the charging tasks and avoid congestions or breakdowns of the power distribution system. The parking reservation system will facilitate their mission to predict very short-term electricity demand and to implement a price policy that will affect drivers' choice and shift their charging needs to off-peak periods. As it was explained in section 1.2, the aim of this thesis was to develop an integrated parking and charging facility management solution for parking operators and CSPs. In this way, both the transport system and the power system could benefit, for example with relief from traffic congestion and reduction in parking search times for the first and with prevention of transformer malfunctions or breakdowns for the second.

7.2 Summary and conclusions

In this thesis, the role of demand for an integrated system of power and transport networks is investigated through the design of hypothetical out-of-home charging situations under a reservation-based policy and the observation of individual choices.

A modelling framework has been developed that integrates parking and travel/activity scheduling in the context of charging services for EV drivers. This approach allows the investigation of interrelationships between the charging process itself and typical travel-timing decisions. The latent class formulation that was presented in subsection 4.2.4 enables the segmentation of the market, which is indispensable for the revenue management application of Chapter 6. With the proposed model it is possible to capture trade-offs between charging price, duration, location and modifications of travel time. Furthermore, the risky choice specifications in section 4.3 were adopted to explain the response to dynamic pricing and to identify the existence of strategic behaviour or, in other words, the willingness of EV drivers to wait for reduced charging prices.

As a result, this framework essentially achieves the specific objectives that were set at the beginning of Chapter 4 and some of the objectives that were established in the introductory chapter. The assumptions that were considered necessary for the modelling of charging behaviour were explained in subsection 4.2.3.

The data required in order to estimate the models described above were collected with the assistance of an online SP survey instrument that was presented in Chapter 3, the EV-PLACE survey. In particular, respondents were faced with two choice experiments: the charging game and the booking game. In the first one, they had to decide between two charging options, assuming that these were the only "offers" provided by the CSP, without the flexibility to alter their charging schedule once they had made their choice. The second experiment was slightly altered so that the additional effort to familiarise with the hypothetical scenarios is minor. The difference with the previous game is that the charging option in the booking game is fixed and the respondents had to choose the time they would make the reservation according to probabilistic predictions of charging prices.

Empirical estimates from the charging game were found to be significant and in agreement with the *a priori* expectations. It is possible that the positive coefficient for charging duration is an effect of the hypothetical scenarios and a misperception that longer charging durations are associated with increased SOC. Nevertheless, if it stands for real-world applications, it gives a higher level of flexibility to the control methods applied by the CSP.

The interaction terms that have been employed to control for demographics and other characteristics have shown a systematic heterogeneity in taste for charging characteristics. On the other hand, the random residual that was modelled with normally distributed coefficients is relatively small. The latent class model has revealed the existence of two distinctive segments of EV drivers: time conscious and price conscious. The class membership probability for these segments is partly affected by latent attributes that express the tendency of users to pre-plan their travel activities.

EUT and non-EUT specifications, based on the booking game, suggested a general tendency towards risk-aversion. Younger, unemployed and individuals with children, i.e. those with higher probability to belong to the time-conscious group demonstrated an increased likelihood to be risk-averse. Non-EUT approaches confirmed the existence of non-linearity in the attitudes towards risk. In particular, individuals were found to slightly underweight outcomes with small probabilities and overweight outcomes with high probabilities. Furthermore, the PT specification indicated that there is a significant difference in how EV drivers perceive gains and losses. Finally, despite the inclination towards risk-aversion, there was still a significant portion of the sample that demonstrated strategic behaviour, a finding that could affect the revenue margins for charging service providers.

The heterogeneity in charging choices that was identified is very significant both from a policy (bottom-up analysis) and from a business (targeted charging services) perspective. By linking the attribute valuations to personal characteristics, it is possible to predict the behaviour of future EV drivers and improve the dynamic pricing tools for CSPs.

The empirical estimates from Chapter 4 are then implemented into SOCSim, a micro-simulation framework that evaluates a demand-driven charging coordination method where the objective is to maximise revenue for the CSP, taking into account the limiting capacity of local power substations. This method is based on mechanisms adopted from the revenue management field. Specifically, two choice-based decentralised approaches were developed and compared with an uncontrolled FCFS simulation: one price-based RM method and one quantity-based RM method. The specific application presented in Chapter 6 is based on a synthesised network for two different regions of London, with increased shopping and working activities respectively. Data were extracted from travel diaries and then scaled up with synthetic population techniques to represent the aggregate effects of EVs charging in the area.

The results for the FCFS system have shown that when the price is spatially differentiated the net revenue for the CSP increases substantially and at the same time charging events are shifted to less congested areas. Also, the nonlinear problem for optimal pricing resulted in higher prices for bundles with higher charging rates, longer charging durations and consumption of peak period resources.

With RM implementation, the spare capacity from the initial negotiations with the DSO is allocated in the most efficient way, leading to the minimisation of imbalance costs. On the other hand, V2G services enable the accommodation of drivers during the peak hours and, thus, the number of allocated drivers increases. Moreover, it reduces the dual prices, partially satisfying the energy requests of EV drivers and mitigating the needs for additional generation capacity. The increase in net revenue for the dynamic allocation algorithm is in the range of 5%-10%, which is in agreement with the applications for other service industries and justifies its adoption from a CSP.

After running a sensitivity analysis for the model it was found that the availability of charging power is a substantial parameter of the optimisation. In addition, it was shown that the CSP could operate with 40% of the assumed charging-post capacity without significant revenue impacts. Finally, it is possible to demonstrate how the uncertainty in choice parameters propagates into the revenue output. For example, charging quantity and price attributes as well as class membership probabilities were found to have a stronger effect for the scenarios with V2G than for the scenarios without V2G.

7.3 Thesis contribution

The added value of the undertaken research can be summarised in the following:

- The development of a survey tool with increased presentational realism, which mimics the environment of a hypothetical online/smartphone application for reservations in advance.
- The provision of the first explicit estimates for out-of-home charging behaviour.
- The integration of charging and parking choices that can be highly interrelated with the increased availability of public charging infrastructure.

- The extension of existing research regarding the response of individuals to the dynamic pricing of electricity, from residential use to the recharging of electric vehicles.
- The treatment of endogeneity between charging control and the disaggregate response of EV drivers.
- The optimization of charging control from the perspective of a charging service provider that has contractual relationships with different parking operators.
- The employment of revenue management methods in a relatively unexplored area and the formation of evidence for their effectiveness.

The scholarly articles that were prepared in the context of the presented research are:

1. Latinopoulos C., Sivakumar A. and Polak, J.W. (2014) Efficient operation of parking facilities under the charging demand of electric vehicles: A Choice-Based Revenue Management approach. Paper presented at the Universities' Transport Study Group Conference, Newcastle.
2. Latinopoulos C., Sivakumar A. and Polak, J.W. (2015) Modelling Joint Charging and Parking Choices of Electric Vehicle Drivers: A Decentralised Control Approach for the Charging Service Provider. Paper presented at the Transportation Research Board 94th Annual Meeting, Washington DC and accepted for publication in Transportation Research Record.
3. Latinopoulos C., Sivakumar A. and Polak, J.W. (2015) Using a Stated Preference survey to understand the response of EV drivers to the dynamic pricing of recharging in parking facilities. Paper presented at the 14th International Conference on Travel Behaviour, Windsor, UK.
4. Latinopoulos C. (2016) Smart services for electric vehicles in parking facilities: empirical results and recommendations for charging service providers. Paper presented at the Universities' Transport Study Group Conference, Bristol.

7.4 Future work

Some of the main limitations of this study have been highlighted throughout the dissertation and they could be used as the basis for future research. For example, the design of the SP exercises in the form of binary choice is not representative of an online reservation environment. The design of an interactive interface where EV drivers will have the opportunity to search, sort or filter the charging options, based on their preferences, will increase the level of engagement with the survey tool and, at the same time, it will allow the examination of underlying behavioural aspects, like for example the searching process of customers.

Furthermore, the booking game is missing an additional dimension of uncertainty, this of future charging post availability. As it was explained in Chapter 3, an additional attribute in this direction would most certainly compromise the level of understanding, and hence the validity of the data collected from the respondents. In a future scenario where the familiarity with dynamic pricing is increased, the researchers could gain valuable insights with the extension of the developed choice experiment.

In terms of the sampling strategy, the low penetration of EVs in the British market together with the great difficulty in tracing their drivers resulted into a somewhat limited pool of respondents with charging experience. As a result, the sample was complemented with individuals that are potential future buyers of EVs. Moreover, it is difficult to generalise the empirical results and come up with concrete assumptions regarding the charging behaviour in other countries. Nevertheless, the experience gained could be used as a guideline for future data collection methods, especially after a certain growth in EV sales.

One limitation that was mentioned in subsection 4.2.3 is that for both SP exercises the energy amount of the charging options is exogenously defined by the charging service provider. As a result, the respondents do not choose how much energy they want for their vehicle, but given a specific SOC, they choose among alternative ways to achieve it. This simplification was considered necessary in order to estimate the parameters for the choice-based RM problem. However, the identification of energy quantity preferences with a discrete/continuous modelling framework would be an interesting topic for future research.

The deployment of the developed behavioural models for forecasting purposes should ideally be cross-validated with RP data when they are available to the researchers. The reason is that some properties of the hypothetical scenarios (e.g. dynamic pricing or pricing workplace charging services) are not established at the moment and individuals might perceive them in a different way. Apart from validation, it would be possible to jointly estimate RP and SP data so that the drawbacks of the latter are mitigated.

The joint modelling of parking and charging choices could be extended to incorporate some of the additional variables that were listed in subsection 2.3.3. For example, sensitivity to cruising time for EVs might differ from conventional vehicles due to the limited range and the significant difference in fuel price.

Finally, the extended RM framework where customers are forward-looking and they strategize their purchase time based on their anticipation of future prices was out of the scope of this thesis and thus it was only presented on a theoretical basis. Nevertheless, since it was shown that the implementation of revenue management for charging services has multiple possibilities and estimates for the response to dynamic pricing are readily available, it could be considered as the next step for future analyses.

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Appendix A: Focus Group

The 11 questions that have been discussed during the focus group at the Centre for Transport Studies at Imperial College are presented below:

1. What is your previous experience with electric vehicles? Do you know people in your near environment that drive an EV? Would you consider buying one in the future and why is that?
2. What do you believe about the range of an electric vehicle? Would it be adequate for your needs? And if you had an EV do you think that it would be your main vehicle?
3. Moving now to the survey what was your general experience with it? What were the main problems that you have encountered and if you could build a new interface from the beginning, how would this look?
4. Here is the part where you have to indicate how your previous day looked like. First of all is anyone who has experienced any problems here? If not, do you believe that you were covered by your final selection?
5. After this point, you had to make selections for another, hypothetical, person rather than for yourself. How do you believe this affected your way of thinking? Did you feel less responsible for the outcomes or did your choices have a certain level of empathy?
6. Here you were presented with a fictional reservation system for charging posts. How useful did you find this description in the context of the following game? How realistic does it look to you and does it remind you of any other online services that you have used in the past?
7. Then there are the instructions of the game itself. We have tried to make this transition from the reservation system to the table that would be the interface for the game. In terms of clarity, how much would you rate this description from 1 to 10? Which part was the most difficult to understand?
8. Moving to the part that you answered to the nine choice tasks, even though you are not an electric vehicle driver, which attribute do you think would affect your decision the most? Did it help you that the scenario was always on top of the two alternatives and if not why?
9. Here we are talking about airline tickets and hotel rooms. Would you call this part distracting or helpful to understand the booking game later? How possible would you consider to make this sort of decisions yourself?

10. In the choice tasks of the booking game, you were presented with some probabilities for future prices or future charging post availability. Here are two different ways of showing the same case (*slide with demonstration*). Which of them do you feel most comfortable with?
11. Is there something else that you would like to know personally from a typical charging experience of an electric vehicle driver? What would you ask them if you wanted to buy an electric vehicle?

The slide that was shown to the participants for question 10 is demonstrated in Figure A.1.

Figure A.1: Alternative ways to illustrate probability distributions for the booking game – Slide presented to the participants of the focus group at the Centre for Transport Studies at Imperial College

Appendix B: Estimation of alternative specifications and comparison of models

Table B.1: MNL charging choice, "charging game" – final specification with interaction terms and sample split among different recruitment channels

Variables	Internal recruitment			Panelbase		
	Coeff.	Std error	p-value	Coeff.	Std error	p-value
ASCA	-0.012	0.169	0.95	0.262	0.083	0.00**
ASCB	0	fixed	***	0	fixed	***
CP [£]	-3.76	1.06	0.00**	-0.649	0.479	0.18
CP * Age<39 [£]	0.624	0.360	0.08*	0.238	0.170	0.16
CP * Having Children [£]	0.465	0.325	0.15	0.037	0.157	0.82
CP * Employed [£]	-1.21	0.517	0.02**	-0.0163	0.229	0.94
CP * EV Loyal Enthusiasts [£]	0.981	0.403	0.02**	0.077	0.184	0.68
CP * Longest distance driven between charging events < 20 miles [£]	-0.240	0.777	0.76	-0.517	0.272	0.06*
CP * Work Based Tour [£]	0.779	0.524	0.14	0.085	0.173	0.62
CP * Initial SOC [£ * miles]	0.327	0.202	0.11	-0.012	0.100	0.91
WT [mins]	-0.299	0.088	0.00**	-0.092	0.033	0.01**
WT * Married or Domestic partnership [mins]	0.053	0.063	0.40	0.033	0.019	0.09*
WT * Living alone [mins]	0.023	0.068	0.73	0.055	0.028	0.05**
WT * Free EV charging [mins]	0.067	0.077	0.38	0.039	0.080	0.63
WT * Charging out of home [mins]	0.067	0.035	0.06*	0.013	0.019	0.50
WT * Weekday travel [mins]	0.035	0.038	0.36	0.033	0.021	0.11
WT * Number of daily activities [mins]	0.058	0.025	0.02**	-0.020	0.015	0.17
CD [mins]	0.025	0.020	0.20	0.016	0.0084	0.05**
CD * Female [mins]	0.011	0.016	0.51	0.0016	0.0033	0.62
CD * Employed [mins]	0.0039	0.0040	0.34	0.0034	0.0023	0.14
CD * Ethnicity [mins]	-0.0046	0.017	0.79	-0.0089	0.0041	0.03**
CD * Number of profile searches [mins]	-0.0073	0.0040	0.07*	-0.014	0.0052	0.01**
CD * Driving distance before charging [mins]	-0.0028	0.0015	0.06*	-0.0009	0.0008	0.25
CD * Number of daily activities [mins]	0.0048	0.0053	0.36	0.0015	0.0028	0.59
CISDE(t_0)[mins]	-0.041	0.012	0.00**	-0.023	0.0089	0.01**
CISDE(t_0) * Education–University [mins]	0.027	0.014	0.05**	0.0040	0.0062	0.52
CISDE(t_0) * Income – Very High [mins]	-0.027	0.017	0.10*	-0.0066	0.011	0.53
CISDE(t_0) * EV Access [mins]	-0.041	0.012	0.00**	-0.0039	0.0075	0.60
CISDE(t_0) * EV Loyal Enthusiasts [mins]	0.0083	0.016	0.60	0.026	0.100	0.01**
CISDE(t_0) * Driving EV more than one year [mins]	-0.022	0.012	0.06*	-0.037	0.012	0.00**
CISDE(t_0) * Driving distance after charging [mins]	0.0092	0.0023	0.00**	0.0003	0.0013	0.81
CISDE(t_0) * Work based tour [mins]	-0.063	0.018	0.00**	0.015	0.0073	0.04**
Number of estimated parameters	31			31		
Number of individuals	37			81		
Number of observations	333			729		
Null log-likelihood	-230.818			-505.304		
Final log-likelihood	-128.822			-431.059		
Likelihood ratio index $\boldsymbol{\rho}$	0.442			0.147		
Adjusted likelihood ratio index $\bar{\boldsymbol{\rho}}$	0.308			0.086		

Table B.2: PLC charging choice, "charging game" – latent class model

Variables		Time-conscious users		Price-conscious users	
Random Utility Model		Coefficient	Std. error	Coefficient	Std. error
ASCA		1.13**	0.470	0.103	0.151
ASCB		0	***	0	***
CP [£]		-0.952**	0.484	-1.54**	0.311
CP * Work based tour [£]		0.598	0.646	0.497	0.326
WT [mins]		-0.103	0.150	-0.144**	0.0597
WT * Travel Profile – Weekday [mins]		-0.0638	0.115	0.0532	0.0365
WT * Number of activities [mins]		-0.0675	0.0647	0.0423	0.0316
CD [mins]		-0.0189	0.0127	0.0103**	0.0030
CISDE(t_0)[mins]		-0.0703**	0.0210	-0.0231**	0.0058
Scale for recruitment channel (η)		0.376**	0.0736	0.376**	0.0736
Class Membership model					
Constant		5.94*	3.53		
Female		-0.551	1.11		
Age less than 40		1.25	1.47		
Married		-2.48**	1.17		
Employed		-2.39*	1.43		
Very High Income		-0.118	1.09		
Ethnicity: White		1.23	0.41	Reference class	
Having children		2.65**	1.14		
Living alone		-2.39	1.88		
Owning or leasing an electric vehicle		-0.930	1.13		
Driving EV more than one year		1.99	0.21		
Charging out of home		-0.705	1.26		
Pre-Planning		-0.428**	0.202		
Number of estimated parameters	30				
Number of individuals	118				
Number of observations	1062				
Null log-likelihood	-736.122				
Final log-likelihood	-601.613				
Likelihood ratio index ρ	0.183				
Adjusted likelihood ratio index $\bar{\rho}$	0.142				

Table B.3: PLC charging choice, "charging game" – restricted latent class model

Variables		**Time-conscious users**		**Price-conscious users**	
Random Utility Model		Coefficient	Std. error	Coefficient	Std. error
ASCA		0.866**	0.325	0.0813	0.157
ASCB		0	***	0	***
CP [£]		-0.769*	0.401	-1.43**	0.276
CP * Work based tour [£]		0.388	0.472	0.279	0.307
WT [mins]		-0.309**	0.150	-0.121**	0.0511
WT * Travel Profile – Weekday [mins]		0.0834	0.0808	0.0394	0.0351
WT * Number of activities [mins]		0.0309	0.0380	0.0441	0.0290
CD [mins]		-0.0133*	0.0076	0.0115**	0.0034
CISDE(t_0)[mins]		-0.0527**	0.0125	-0.0220**	0.0057
Scale for recruitment channel (η)		0.412**	0.0713	0.412**	0.0713
Class Membership model					
Constant		-0.184	1.62		
Female		-0.784	0.857		
Age less than 40		0.589	0.775		
Married		-2.50**	1.27		
Employed		-1.66**	0.819	Reference class	
Very High Income		0.760	0.982		
Ethnicity: White		1.19	1.18		
Having children		2.03**	0.950		
Living alone		-1.70	1.20		
Number of estimated parameters	26				
Number of individuals	118				
Number of observations	1062				
Null log-likelihood	-736.122				
Final log-likelihood	-607.745				
Likelihood ratio index $\boldsymbol{\rho}$	0.174				
Adjusted likelihood ratio index $\bar{\boldsymbol{\rho}}$	0.139				

The non-nested statistical test that is used to compare the mixed logit model with the two latent class specifications above, was introduced by Ben-Akiva and Swait (1986) and it can be described as follows: if Model 2 (Mixed logit) is the true model, the probability that the adjusted likelihood ratio index of Model 1 (Latent class) is greater than that of Model 2 is asymptotically bounded by the following function:

$$\Pr(|\varrho_2^2 - \varrho_1^2|) \geq Z) \leq \Phi(-\sqrt{-2ZL(0) + (K_1 - K_2)}) \qquad \text{(B.1)}$$

where Z is the absolute difference between the fitness measures, $L(0)$ is the initial log-likelihood of the models, Φ is the standard normal cumulative distribution (CDF), and K_1 and K_2 are the numbers of estimated variables for Model 1 and Model 2 respectively. From Table B.3, it can be deduced that $P \leq \Phi(-5{,}934) \approx 0$ for the PLC model and $P \leq \Phi(-5{,}970) \approx 0$ for the PLC restricted model. Since the equation above defines the upper bound of the probability that Model 1 is incorrectly selected as the true model while the true model is Model 2, it can be concluded that the mixed logit is superior to both the latent class specifications.

Table B.4: Statistical comparison of mixed logit and latent class models

Models	**Mixed Logit**	**PLC**	**PLC restricted**
No of parameters	36	30	26
Initial LL	-736.122	-736.122	-736.122
$\boldsymbol{\bar{\rho}}$	0.170	0.142	0.139
$-\sqrt{-2ZL(0)+(K_1-K_2)}$	-	-5,934	-5,970

Appendix C: Summary of EV charging operation modelling studies

The abbreviations for Table C.1 are given below:

Analysed effects

{LC/DG: Local constraints for distribution grids (e.g. bottlenecks, transformer failures etc.), LF/DT: Lifecycle of distribution transformers, EG: Electricity generation, H&M/VG: High and medium voltage grids, EA: Environmental analysis, FR: Frequency regulation, PL-R: Parking lot revenue, RI: Renewable Integration, CC: Cost of charging}

Optimization method

{LR: Lagrangian Relaxation, MAS: Multi-agent systems, PSO: Particle Swarm Optimization, FL: Fuzzy Logic, SG: Stochastic game, LP: Linear Programming, QP: Quadratic Programming, DP: Dynamic Programming, SB: Simulation-based, AU: Auction-based mechanisms, ABM: Agent-Based Model, OPF: Optimal power flow model, RM: Revenue Management, CP: Convex programming}

NA stands for non-applicable or not clearly mentioned in the study.

Table C.1: Modelling of charging operation for electric vehicle studies

STUDIES	VEHICLE MIX	DRIVING PROFILES	CHARGING INFRASTRUCTURE	SOC ASSUMPTIONS	CHARGE POTENTIAL (LOCATION)	CHARGING COORDINATION	ANALYSED EFFECTS	GEOGRAPHIC FOCUS	ELECTRICITY BASE LOAD	CHARGING BEHAVIOUR	V2G SERVICES	METHOD/ OBJECTIVE
Acha et al. (2010)	10% or 30% PHEV penetration	Exogenous (NHTS)	NA	Vehicles must be fully charged by early morning	Exogenous (NHTS)	Centralised	LC/DS & EG	Small radial network	Half-hourly intervals, winter period, UK distribution system	Three exogenous scenarios (only in low power demand periods, more flexible, no constraints)	YES	OPF (Multi-objective optimisation)
Acha et al. (2012)	Nissan Leaf, 24kWh and 97 miles range (No variation in battery capacity and energy consumption)	1) Agent-based 2) Battery is never depleted in a single day	240V/16A chargers (maximum rate 3.84kW)	Batteries are fully charged by 06:00 am on weekdays and 08:00 am on weekends	Agent-based	Centralised	LC/DS & EA & CC	City level	Half-hourly intervals, winter period, UK distribution system	Agent-based, Driven by optimal control	NO	ABM & OPF
Biviji et al. (2014)	NA	NA	NA	NA	NA	NA	NA	California and Portland	NA	Revealed preferences: hourly average charging profiles with various pricing schemes	NA	NA
Caramanis and Foster (2009)	50 EVs	Drivers provide information about their departure time	Charging rate: 2kW	NA	NA	Centralised	RI & LC/DG	Texas	Typical Autumn and summer residential profiles	Charging rate changes between 0 and a fixed value Assumptions about charging demand	NO	DP Objective: Optimal schedule and clearing prices
Clement-Nyns et al. (2009)	Four PHEV penetration levels	Randomly allocated	Charging rate: 4 kW	Vehicles are fully charged at the end of each event	Home charging	Centralised	LC/DS	Residential network in Belgium	Two groups of summer and winter profiles (15-min intervals) – normally distributed for SP	Four charging periods Uncoordinated charging or Coordinated charging	NO	QP or SP Objective: Minimise power losses
Daina 2014	24kWh battery capacity	Constructed for SP survey	Maximum rate 7.2kW	NA	Only home charging	NA	NA	UK	NA	Endogenous Joint choice of charging and travel timing	NO	NA
De Gennaro et al. 2013	Six types of BEVs (energy consumption from real test-drives)	1) GPS-based for conventional vehicles 2) More than 50% of the trips in the province boundaries	Charging efficiency: 95% Two scenarios 1) AC, single phase, 3.3kW, 2kW rate 2) DC, 55kW, 40 kW rate	1)Minimum SOC: 20% 2)Maximum SOC: 95% 3) Battery fully charged at the beginning of the analysis period	Driven by GPS data	NA	EG	Modena, Italy (2,688 km^2)	Italian electric energy consumption	Twelve charging strategies (non-aggressive vs aggressive, on-peak vs off-peak, indirect vs direct)	NO	NA

Table C.1: Modelling of charging operation for electric vehicle studies (Continue)

STUDIES	VEHICLE MIX	DRIVING PROFILES	CHARGING INFRASTRUCTURE	SOC ASSUMPTIONS	CHARGE POTENTIAL (LOCATION)	CHARGING COORDINATION	ANALYSED EFFECTS	GEOGRAPHIC FOCUS	ELECTRICITY BASE LOAD	CHARGING BEHAVIOUR	V2G SERVICES	METHOD/ OBJECTIVE
Dong and Lin 2014	BEV range modelled with Weibull distribution	GPS-based longitudinal travel data from conventional vehicles	NA	Vehicles fully charged by morning	Two scenarios 1) Once per day, only at home 2) Within-day charging available	NA	NA	Seattle, Washington metropolitan area	NA	Stochastic: Distance between charges is modelled with a compound Poisson-gamma distribution	NO	NA
Flath et al. (2012)	200 EVs (90% regular customers, 10% spot customers) Energy consumption 0.2 kWh/km	Reflected by charging amounts (mean: 40 km for regular and 80 km for spot customers)	NA	Battery discharge is Gamma-distributed	Home charging	Decentralised	LD/DS	Suburban neighbourhood	NA	Charging at constant rate over a fixed period (Overnight at home) Random charging demands (Erlang distributed)	NO	RM Objective: Maximise social welfare
Flath et al. (2013)	Battery capacity: 30kWh Energy consumption: 0.15kWh/km	Empirical driving behaviour for conventional vehicles (German Mobility Panel)	Charging rate: 11kW (165 minute for full recharge)	Minimum SOC that triggers charging activity for the heuristic (30%)	Home and work charging	Decentralised	LC/DS & CC	Germany	NA	1) Naïve charging 2) Optimal smart charging 3) Heuristic smart charging	NO	LP Endogenous locational pricing Objective: Minimise cost for the driver
Franke and Krems 2013c	Converted MINI Cooper (168km-250km range)	Revealed preferences and travel diaries	32A	Revealed preferences, charging diaries and questionnaires	Home-based and 50 public charging stations	Centralised	RI	Metropolitan area of Berlin, Germany	NA	Revealed preferences, charging diaries and questionnaires	NO	Objective: Minimise excess energy from wind
Galus et al. 2010	30,000 PHEVs (30 kWh battery)	Transport micro-simulation	3.5 kW connection	Vehicles are connected at the beginning and at the end of the day (SOC between 20% and 100%)	Home and work charging	Decentralised	EG	City level	Residential base load	Control driven and stochastic changes	YES	SB
Galus et al. 2012	1) Vehicle technology assessment model (VTAM) 2) Regression models for energy consumption	Multi-agent based	NA	Agent-based	Available at home and working locations	Centralised	LC/DS & CC	Zurich, Switzerland	Power system simulation	Agent-based, driven by charging coordination	NO	SC (Multi-objective optimisation)

Table C.1: Modelling of charging operation for electric vehicle studies (Continue)

STUDIES	VEHICLE MIX	DRIVING PROFILES	CHARGING INFRASTRUCTURE	SOC ASSUMPTIONS	CHARGE POTENTIAL (LOCATION)	CHARGING COORDINATION	ANALYSED EFFECTS	GEOGRAPHIC FOCUS	ELECTRICITY BASE LOAD	CHARGING BEHAVIOUR	V2G SERVICES	METHOD/ OBJECTIVE
Hadley (2007)	One million PHEVs (four vehicle types) Future sales projection	NA	Power connections: 1) 1.4kW 2) 2kW 3) 6kW	Vehicles can be fully discharged and charged	Home charging	NA	EG & EA & CC & H&M/VG	Virginia-Carolinas electric grid	Combination of hourly loads from different utilities (Future projection for peak and off-peak seasons)	Charging start 1) Early evening 2) Later at night	NO	NA
Han et al. (2010)	Battery capacity: 20kWh	Drivers notify the operator for the next trip	Maximum rate (charging and discharging): 2kW	Target SOC (point value) is above the initial charge	NA	Centralised	FR	NA	NA	Plug-in duration: 12h	YES	DP Objective: Optimise sequence of charging and discharging events
Hartmann and Özdemir (2011)	VW-GOLF specifications Storage capacity of EVs: 32.8kWh Various EV penetration scenarios	Average driving statistics (41.9 km) Plug-in availability simulated from German mobility data	Standard sockets: 230V Max rate: 3.6kW Energy efficiency: 90%	The battery can be discharged down to the level that covers average driving distance	NA	Decentralised	FR & CC	Germany	Fluctuations from average electricity demand (least square value)	Three charging/ discharging strategies 1) Unmanaged 2) Grid-stabilising V2G 3) Profit maximising V2G	YES	SB
Hashimoto et al. (2013)	Battery capacity:20 kWh (approx. 200km) Different penetration levels of EVs	Actual parking data Changes in parking times based on survival analysis	NA	NA	Out-of-home parking lot	Decentralised	PL-R	Parking lots	NA	Parking data & Survival analysis Randomly allocated energy between 1kWh and 10kWh	YES	AU Objective: Maximise parking revenue
He et al. (2012)	200EVs Chevrolet Volt specifications Battery capacity (16kWh)	Uniform arrival distributions	Max rate: 5 kW	Uniform distribution of initial SOC (0%-80%)	NA	Centralised	CC	Small geographic area (micro-grid), Canada	1) Scale down the real load of Toronto 2) Forecast with regression	Uniform distribution of charging periods (4-12 hours)	YES	1) Global scheduling 2) Local scheduling CP Objective: Minimise total cost for charging EVs
Huang et al. 2012	Nissan Leaf (Temperature dependent range)	Four-step model	Level 1, Level 2 and Level 3	EVs start charging below 20%	Pre-selected charging locations (public chargers included)	NA	EG	Indianapolis metropolitan area	Agent-based residential demand	Quantity of charging depends on trip length. Time of charging depends on OD matrix. Two strategies	NO	NA

Table C.1: Modelling of charging operation for electric vehicle studies (Continue)

STUDIES	VEHICLE MIX	DRIVING PROFILES	CHARGING INFRASTRUCTURE	SOC ASSUMPTIONS	CHARGE POTENTIAL (LOCATION)	CHARGING COORDINATION	ANALYSED EFFECTS	GEOGRAPHIC FOCUS	ELECTRICITY BASE LOAD	CHARGING BEHAVIOUR	V2G SERVICES	METHOD/ OBJECTIVE
Hübner et al. 2013	Mixture of commercially available vehicles	GPS and CAN data (Comparison with NTS)	AC (3,7 and 22kW) DC (50kW)	NA	Domestic, Public and workplace charging stations	NA	NA	North East England (400,000 miles coverage)	NA	GPS and CAN data and questionnaires	NO	NA
Hutson et al. (2008)	Battery capacity (10-25 kWh) Three EV penetration levels	Arrival and departure times uniformly distributed	Efficiency: 80% - 95%	Desired SOC at departure: 60%	Out-of-home parking lot	Centralised	PL-R	California	Indirectly expressed through hourly prices from the system operator (winter and summer day)	Driven by charging coordination	YES	PSO Objective: Optimal sequence of buy and sell periods
Kamboj et al. (2011)	5 EVs (+20 EVs in second stage) Battery capacity: 35kWh	Next trip is predicted based on past driving patterns	125V/15A 208V/50A (Occasionally 80A) max rate 19.2kW	When the SOC is minimum the vehicle cannot discharge	NA	Decentralised	FR	PJM (TSO in the US)	NA	Charging always start at a minimum SOC Driven by regulation	YES	MAS
Kang and Recker 2009	PHEV20 and PHEV60 (without blended operation)	Activity-based patterns for conventional vehicles	120V, 15A (82% efficiency) 240V, 40A (with upgrade and 87% efficiency)	Battery efficiency is 85%.	Home and public locations (Based on the scenario)	Centralised	EA & EG	California	Forecasts based on California electricity data	Four scenarios 1) End of day 2) Uncontrolled home charging 3) Controlled charging (after 10pm) 4) Public charging availability	NO	NA
Kempton and Letendre 1997	Three EV types with three battery settings	Driving data	AC, 220V,40A, 3-phase (discharge allowed – up to 8 kW from the EV)	32km buffer always remain in the battery	NA	Centralised	EG & CC & RI	Southern California	NA	Auto-charge controller with charge and discharge options and inputs for travel needs and constraints	YES	NA
Knapen et al. 2012	BEVs and PHEVs (categories: small, medium and large), shares from conventional vehicles	Activity-based	3.3kVA and 7.2kVA (Home charging stations depend on vehicle category)	Everyday charging due to range anxiety	Home charging with additional charging events at workplaces	NA	EG	Flanders, Belgium (13,000 km^2)	Aggregated time-of-day electricity consumption for the whole country	Activity-based Four scenarios 1) Night charging 2) Uniform charging, off-peak 3) Charge after arriving at home (last trip) 4) Charge after arriving at home (always)	NO	NA

Table C.1: Modelling of charging operation for electric vehicle studies (Continue)

STUDIES	VEHICLE MIX	DRIVING PROFILES	CHARGING INFRASTRUCTURE	SOC ASSUMPTIONS	CHARGE POTENTIAL (LOCATION)	CHARGING COORDINATION	ANALYSED EFFECTS	GEOGRAPHIC FOCUS	ELECTRICITY BASE LOAD	CHARGING BEHAVIOUR	V2G SERVICES	METHOD/ OBJECTIVE
Lemoine et al. 2008	PHEVs (all-electric or blended mode) Different scenarios for PHEV penetration	Driving distances depend on the charging scenarios	AC, 120V Rate:1kWh/h Efficiency: 82%	NA	Home and workplace	Centralised	EG	California	Supply bids and hour-based market-clearing electricity demand	Three scenarios 1) Once each day (optimal charging) 2) Once each day (Evening charging) 3) Twice each day (Morning and evening)	NO	NA
Letendre and Watts (2009)	Three PHEV penetration scenarios (20 miles range) Four vehicle fleet alternatives	Uniform distribution of arrival times	Rate: 1.4 kW Charging efficiency: 82%	NA	Home and workplace	Centralised	EG	Vermont	Peak summer and winter seasons	Fixed charging duration (6h) – Four charging strategies	NO	NA
Lund and Kempton (2008)	80% of vehicles are parked at rush hours Motivation for plugging-in 70% of the parking time 100% EV penetration	Estimated from Danish statistics. Distribution of travel demand gives input for plug-in times	High power line connections: 10kW Efficiency: 90%	Batteries are fully charged before next driving event	Home, employer lots, mass transit stations etc.	Decentralised	RI & EA	Two national energy systems (one without CHP and one based on Denmark)	NA	From Driving statistics Two peak demand periods: (07:00 am – 09:00 am and 16:00 pm – 18:00 pm)	YES	SB
Ma et al. (2010)	30% EVs of the total vehicle fleet Battery size:10kWh	NA	Charging efficiency: 85% Max rate: 3kW	Initial SOC: 15%	NA	Decentralised	EG & CC	NA	Typical summer load curve	Infinite population limit (solution of a fixed point problem)	NO	SG Objective: Minimisation of operation cost
Mets et al. (2010)	Chevrolet Volt specifications Three penetration scenarios	Statistical model	NA	Battery has to be fully charged for departure	Home charging	Centralised	EG	Belgium	Synthetic load profiles (two winter days)	Defined by control strategies	NO	QP
Mirzaei et al. (2014)	All EVs have equal battery capacity: 50kWh	Historical parking data. Random arrival and departure times	NA	If the SOC is not provided the parking operator pays a penalty Initial SOC: 15%-100%	Out-of-home parking lot	Decentralised	PL-R & CC	Livermore, Almeda county, California	Day-ahead prices for the following 24-h period are provided to the parking operator	Driven by optimal scheduling of charging and discharging	YES	PSO Objective: Maximize parking lot and vehicle owners' profit
Mullan et al. 2011	EV take-up increases with 5% of the total vehicle fleet	Average driving statistics	12 Level 2 chargers (7.7.kW)	NA	Only home charging	Centralised	EG	Western Australia	Actual load data from Western Power	Three charging scenarios 1) Evening charging 2) Night charging 3) Controlled night charging	NO	NA

Table C.1: Modelling of charging operation for electric vehicle studies (Continue)

STUDIES	VEHICLE MIX	DRIVING PROFILES	CHARGING INFRASTRUCTURE	SOC ASSUMPTIONS	CHARGE POTENTIAL (LOCATION)	CHARGING COORDINATION	ANALYSED EFFECTS	GEOGRAPHIC FOCUS	ELECTRICITY BASE LOAD	CHARGING BEHAVIOUR	V2G SERVICES	METHOD/ OBJECTIVE
Papadaska-lopoulos and Strbac 2011	Energy consumption: 0.15kWh/km 10% EV penetration Max battery capacity: 15kWh	Driving patterns adopted from previous studies (journey types, start and end time, distance)	Maximum rate: 3KW	The starting SOC is 50% of the maximum battery capacity	NA	Decentralised	EG & CC	UK	Typical winter day, UK system	Four scenarios: Dumb charging and three levels of charging flexibility	NO	LR & LR heuristics Objective: Maximise social welfare (Market clearance)
Papadaskal opoulos and Strbac (2012)	Energy consumption: 0.15kWh/km 20% EV penetration Max battery capacity: 15kWh	Driving patterns adopted from previous studies (journey types, start and end time, distance)	Maximum rate: 3KW	Inflexible EVs start the day with 100% SOC	Home charging	Decentralised	EG & CC & H&M/VG	UK	Typical winter day and wind profiles, UK system	Four scenarios: Dumb charging and three levels of charging flexibility	NO	LR & LR heuristics Objective: Maximise social welfare (Market clearance)
Pecas Lopes et al. (2009)	PHEVs and two types of BEVs Five EV penetration scenarios (from 0% to 52%)	NA	NA	Target battery levels are defined by the EV owners	NA	Decentralised	LC/DS	Residential areas in Portugal	Typical load profiles from residential, commercial and industrial customers	1) Dumb charging 2) Dual-tariff policy 3) Smart charging	NO	SB Objective: Maximise EV integration
Perujo and Ciuffo 2010	Three vehicle types Estimation based on historical trends	Uniform distribution of plug-in times OD matrices for trips	90% charging efficiency	Not all vehicles charge every day The average percentage of charging vehicles is constant	Only home charging	NA	EG & EA	Province of Milan, Italy	Daily base loads from Italian national grid	Average 5h charging time 10min charging time for some car models	NO	NA
Rahman and Shrestha (1993)	Expert opinions (Scenarios for penetration level and energy consumption)	Driving distance Assumptions	NA	NA	NA	NA	LC/DS	Blacksburg, Virginia	15-minute intervals for residential area and campus	(Automatic regulated charge) Three charging strategies	NO	NA
Richardson et al. (2010)	Various penetration levels of EVs	NA	Single phase, AC	NA	Home charging	NA	LC/DS	Dublin, Ireland	15-minute intervals for residential load from DSO (profiles randomly assigned to test network)	Typical 3.5kW demand for battery	NO	NA
Robinson et al. 2013	44 EVs	Data loggers and GPS (Comparison with NTS)	1) 91 3kV home chargers 2) 268 3kV public/work chargers 3) 8 50 kV public/work chargers	NA	Home, work, public and other charging	NA	EA	North East of England	Half-hourly intervals, winter period, UK (National Grid)	Data logger, GPS, and focus groups	NO	NA

Table C.1: Modelling of charging operation for electric vehicle studies (Continue)

STUDIES	VEHICLE MIX	DRIVING PROFILES	CHARGING INFRASTRUCTURE	SOC ASSUMPTIONS	CHARGE POTENTIAL (LOCATION)	CHARGING COORDINATION	ANALYSED EFFECTS	GEOGRAPHIC FOCUS	ELECTRICITY BASE LOAD	CHARGING BEHAVIOUR	V2G SERVICES	METHOD/ OBJECTIVE
Roe et al. (2009)	Battery capacity 18kWh Three scenarios of PHEV penetration	Driving distance assumptions	1) 120V, 15A 2) 240V, 30A 96% efficiency	Vehicles fully discharged at the start of the simulation period	Home charging	NA	1) LF/DT 2) EG	Low voltage distribution system and power system	Random daily load	Three charging scenarios 1) 21:00 pm – 08:00 am 2) 00:00 pm – 03:00 am 3) Probabilistic distribution	NO	NA
Rotering and Ilic (2011)	PHEV battery capacity: 4.5kWh	Future driving profiles are assumed to be known (travel time, distance)	Max rate: 4kW	SOC is 100% before the first trip of the day	NA	Centralised	FR & CC	California	Reflected by electricity price for summer and autumn typical days	Driving statistics	YES	DP Objective: Optimise sequence of battery states
Saber and Venayaga-moorthy (2009)	50,000 vehicles max battery capacity: 25kWh	NA	Efficiency 85%	Departure SOC: 50%	Out-of-home parking lot	Centralised	CC	Constrained parking lot	Load demand adopted from previous study	Charge at off-peak load and discharge at peak loads	YES	PSO Objective: Minimise total running costs
Schey et al. 2012	Nissan Leaf	Based on real mobility data	1) AC Level 2 residential, 240V, up to 7.2 kW charging rate	NA	Home and public infrastructure	NA	NA	Nashville and San Francisco	NA	Charging demand and charging availability defined by revealed preferences	NO	NA
Schieffer (2011)	Chevrolet Volt and Nissan Leaf settings	Transport micro-simulation	Standard 3.5 kW rate	Battery SOC should remain between 10% and 90% Buffer level is 0%	Home and work charging locations	Decentralised	FR & CC	Berlin	Typical residential profile	Probability density functions for charging timing	YES	LP Multi-objective optimisation
Schneider et al. (2008)	Battery size (10kWh) Various penetration levels of PHEVs	Average driving distances (53km)	1) 120V, 15A 2) 240V, 50A Efficiency: 87%	Full charge/discharge cycle once a day	Home charging	NA	LC/DS	Washington State	Winter load profiles from electric utilities (Western Pacific Northwest and Eastern Pacific Northwest)	1) Smart charging profile from previous study 2) Charge after arrival	NO	NA
Smart et al. 2010	5-kWh blended operation PHEVs (Conversion of Ford Escape Hybrid and Toyota Prius)	Actual vehicle usage (On-board logger)	Level 1 (AC, 120V, 12A)	NA	Home and out-of-home charging	NA	EG	26 US states, 3 Canadian provinces, Finland	NA	Actual vehicle usage (On-board logger)	NO	NA
Sortomme et al. (2011)	Four scenarios of PHEV penetration Battery capacity: 10kWh	Monte Carlo simulation for vehicle allocation	Standard 120V/15A wall outlets	When plugged-in PHEVs are fully discharged	Home charging	Centralised	LC/DG	Two residential distribution systems	One hourly load profile and two synthetic profiles randomly allocated	PHEVs stay connected from 18:00 to 06:00 next day	NO	LP&QP Multi-objective optimisation

Table C.1: Modelling of charging operation for electric vehicle studies (Continue)

STUDIES	VEHICLE MIX	DRIVING PROFILES	CHARGING INFRASTRUCTURE	SOC ASSUMPTIONS	CHARGE POTENTIAL (LOCATION)	CHARGING COORDINATION	ANALYSED EFFECTS	GEOGRAPHIC FOCUS	ELECTRICITY BASE LOAD	CHARGING BEHAVIOUR	V2G SERVICES	METHOD/ OBJECTIVE
Stoeckl et al. (2011)	Three penetration scenarios	Average statistical data (40 km/day)	1) Single phase, 400V, 16A, 3.68kW 2) Three phase, 400V, 16A, 11.09kW 3) 30kW	NA	NA	NA	LC/DS	Bavaria, Germany	NA	Vehicle are charged as soon as they return home	NO	SB
Su and Chow 2010	Large amount of PHEVs	Based on simulator from previous studies	NA	NA	Out-of-home parking lot	Decentralised	LC/DG & EG	Municipal parking deck	Historical load profile for summer	1) TOU 2) Users are paid incentive to avoid peak periods	NO	MAS & FL
Tal et al. 2014	3,500 EVs (Plug-in Prius, Chevrolet Volt, Nissan Leaf)	Self-reported travel patterns	Level 1 at home Level 1 and Level 2 at other locations	Each charging event results into a full battery	Home, work and other public charging locations	NA	NA	California	NA	Self-reported charging patterns	NO	NA
Van Vliet et al. (2011)	Compact 5-seater (50-250 km range) Two EV penetration levels	Average driving statistics	Efficiency: 90% for charging and 96% for discharging	Car is fully charged at the morning	Home and work charging locations	NA	LC/DS	Netherlands (or for the whole EU)	Average daily pattern (2006-2008)	Uncoordinated or off-peak	YES	NA
Vasirani and Ossowski (2013)	Battery capacity uniformly drawn (15-25kWh)	NA	There is one charging spot for each examined EV	Initial SOC when plugged-in: 0%	Home and public charging	Centralised	LC/DS	Typical residential area (Spain)	NA	Charging time window: 12h (08:00pm-08:00am)	NO	SG Objective: Optimal allocation of power to vehicles
Waraich et al. (2013)	Simulation of actual driving cycles	Activity-based	3.5 kW, 240V, 16A, Single phase	Drivers start with a fully charged battery in the morning	Home and work charging locations	Centralised	LC/DS	Berlin, Germany	Power simulation based	Three scenarios 1) Dumb charging 2) Dual Tariff 3) Smart charging	NO	SB
Westerman et al. 2010	50 EVs	Actual vehicle usage	Single phase, 7.3 kW, 32A	NA	Home-based charging	Centralised	RI & EG	Berlin, Germany	Information from the TSOs	Charging frequency, plug-in time, plug-off time from actual vehicle usage	NO	NA
Zhang et al. 2011	PHEV (45 MPG, battery capacity 1-10kWh)	Based on travel survey data (NHTS)	Efficiency 85%	EVs start the day with a 100% SOC	Home, home and work, anywhere	NA	EG	South Coast Air Basin, California	Power demand for extreme summer day	1) Immediate 2) Delayed 3) Average	NO	NA
Zoepf et al. 2013	125 Toyota Prius PHEVs (5.4kWh Li-ion battery)	Data loggers (Compared with NHTS)	Level 1 (110V) Level 2 (220V)	50%: Fully charge 50%: Charge between 0 and 2.5kWh	Home and workplace charging	NA	NA	US	NA	Endogenous: mixed logit for the probability of charging at the end of a trip Capturing heterogeneity	NOs	NA

Appendix D: Consideration Sets for RM

Table D.1: Consideration sets for the customer segments – Without V2G

Segment[1]	Dwelling period	Energy demand	Consideration set[2]
1/33	09:00 am – 10:00 am	6kWh	{1,2,3,4,5,6,7,8}
2/34	09:00 am – 10:00 am	12kWh	{15,16,17,18,19,20,21,22}
3/35	10:00 am – 11:00 am	6kWh	{1,2,3,4,5,6,7,8}
4/36	10:00 am – 11:00 am	12kWh	{15,16,17,18,19,20,21,22}
5/37	11:00 am – 12:00 pm	6kWh	{1,2,3,4,5,6,7,8}
6/38	11:00 am – 12:00 pm	12kWh	{15,16,17,18,19,20,21,22}
7/39	12:00 pm – 13:00 pm	6kWh	{1,2,3,4,5,6,7,8}
8/40	12:00 pm – 13:00 pm	12kWh	{15,16,17,18,19,20,21,22}
9/41	09:00 am – 11:00 am	6kWh	{1,2,3,4,5,6,7,8,9,10,11,12, 13,14}
10/42	09:00 am – 11:00 am	12kWh	{15,16,17,18,19,20,21,22,23,24,25,26,27,28}
11/43	09:00 am – 11:00 am	18kWh	{35,36,37,38,39,40}
12/44	09:00 am – 11:00 am	24kWh	{35,36,37,38,39,40}
13/45	10:00 am – 12:00 pm	6kWh	{1,2,3,4,5,6,7,8,9,10,11,12, 13,14}
14/46	10:00 am – 12:00 pm	12kWh	{15,16,17,18,19,20,21,22,23,24,25,26,27,28}
15/47	10:00 am – 12:00 pm	18kWh	{35,36,37,38,39,40}
16/48	10:00 am – 12:00 pm	24kWh	{35,36,37,38,39,40}
17/49	11:00 am – 13:00 pm	6kWh	{1,2,3,4,5,6,7,8,9,10,11,12, 13,14}
18/50	11:00 am – 13:00 pm	12kWh	{15,16,17,18,19,20,21,22,23,24,25,26,27,28}
19/51	11:00 am – 13:00 pm	18kWh	{35,36,37,38,39,40}
20/52	11:00 am – 13:00 pm	24kWh	{35,36,37,38,39,40}
21/53	09:00 am – 12:00 pm	6kWh	{1,2,3,4,5,6,7,8,9,10,11,12, 13,14}
22/54	09:00 am – 12:00 pm	12kWh	{15,16,17,18,19,20,21,22,23,24,25,26,27,28}
23/55	09:00 am – 12:00 pm	18kWh	{31,32,33,34,35,36,37,38,39,40}
24/56	09:00 am – 12:00 pm	24kWh	{35,36,37,38,39,40,41,42,43,44}
25/57	10:00 am – 13:00 pm	6kWh	{1,2,3,4,5,6,7,8,9,10,11,12, 13,14}
26/58	10:00 am – 13:00 pm	12kWh	{15,16,17,18,19,20,21,22,23,24,25,26,27,28}
27/59	10:00 am – 13:00 pm	18kWh	{31,32,33,34,35,36,37,38,39,40}
28/60	10:00 am – 13:00 pm	24kWh	{35,36,37,38,39,40,41,42,43,44}
29/61	09:00 am – 13:00 pm	6kWh	{1,2,3,4,5,6,7,8,9,10,11,12, 13,14}
30/62	09:00 am – 13:00 pm	12kWh	{15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30}
31/63	09:00 am – 13:00 pm	18kWh	{31,32,33,34,35,36,37,38,39,40}
32/64	09:00 am – 13:00 pm	24kWh	{31,32,33,34,35,36,37,38,39,40,45,46}

[1] The first 32 segments are the price conscious users and the next 32 segments are the time conscious users.
[2] The numbers in brackets correspond to the charging bundles that were defined in Table 6.2.

Table D.2: Consideration sets for the customer segments – WithV2G

Segment[1]	Dwelling period	Energy demand	Consideration set[2]
1/43	09:00 am – 10:00 am	6kWh	{1,2,3,4,5,6,7,8}
2/44	09:00 am – 10:00 am	<1kWh	{47,48,49,50,51,52,53,54}
3/45	09:00 am – 10:00 am	12kWh	{15,16,17,18,19,20,21,22}
4/46	10:00 am – 11:00 am	6kWh	{1,2,3,4,5,6,7,8}
5/47	10:00 am – 11:00 am	<1kWh	{47,48,49,50,51,52,53,54}
6/48	10:00 am – 11:00 am	12kWh	{15,16,17,18,19,20,21,22}
7/49	11:00 am – 12:00 pm	6kWh	{1,2,3,4,5,6,7,8}
8/50	11:00 am – 12:00 pm	<1kWh	{47,48,49,50,51,52,53,54}
9/51	11:00 am – 12:00 pm	12kWh	{15,16,17,18,19,20,21,22}
10/52	12:00 pm – 13:00 pm	6kWh	{1,2,3,4,5,6,7,8}
11/53	12:00 pm – 13:00 pm	<1kWh	{47,48,49,50,51,52,53,54}
12/54	12:00 pm – 13:00 pm	12kWh	{15,16,17,18,19,20,21,22}
13/55	09:00 am – 11:00 am	6kWh	{1,2,3,4,5,6,7,8,9,10,11,12, 13,14}
14/56	09:00 am – 11:00 am	<1kWh	{47,48,49,50,51,52,53,54,55,56,57,58,59,60}
15/57	09:00 am – 11:00 am	12kWh	{15,16,17,18,19,20,21,22,23,24,25,26,27,28}
16/58	09:00 am – 11:00 am	18kWh	{35,36,37,38,39,40}
17/59	09:00 am – 11:00 am	24kWh	{35,36,37,38,39,40}
18/60	10:00 am – 12:00 pm	6kWh	{1,2,3,4,5,6,7,8,9,10,11,12, 13,14}
19/61	10:00 am – 12:00 pm	<1kWh	{47,48,49,50,51,52,53,54,55,56,57,58,59,60}
20/62	10:00 am – 12:00 pm	12kWh	{15,16,17,18,19,20,21,22,23,24,25,26,27,28}
21/63	10:00 am – 12:00 pm	18kWh	{35,36,37,38,39,40}
22/64	10:00 am – 12:00 pm	24kWh	{35,36,37,38,39,40}
23/65	11:00 am – 13:00 pm	6kWh	{1,2,3,4,5,6,7,8,9,10,11,12, 13,14}
24/66	11:00 am – 13:00 pm	<1kWh	{47,48,49,50,51,52,53,54,55,56,57,58,59,60}
25/67	11:00 am – 13:00 pm	12kWh	{15,16,17,18,19,20,21,22,23,24,25,26,27,28}
26/68	11:00 am – 13:00 pm	18kWh	{35,36,37,38,39,40}
27/69	11:00 am – 13:00 pm	24kWh	{35,36,37,38,39,40}
28/70	09:00 am – 12:00 pm	6kWh	{1,2,3,4,5,6,7,8,9,10,11,12, 13,14}
29/71	09:00 am – 12:00 pm	<1kWh	{47,48,49,50,51,52,53,54,55,56,57,58,59,60}
30/72	09:00 am – 12:00 pm	12kWh	{15,16,17,18,19,20,21,22,23,24,25,26,27,28}
31/73	09:00 am – 12:00 pm	18kWh	{31,32,33,34,35,36,37,38,39,40}
32/74	09:00 am – 12:00 pm	24kWh	{35,36,37,38,39,40,41,42,43,44}
33/75	10:00 am – 13:00 pm	6kWh	{1,2,3,4,5,6,7,8,9,10,11,12, 13,14}
34/76	10:00 am – 13:00 pm	<1kWh	{47,48,49,50,51,52,53,54,55,56,57,58,59,60}
35/77	10:00 am – 13:00 pm	12kWh	{15,16,17,18,19,20,21,22,23,24,25,26,27,28}
36/78	10:00 am – 13:00 pm	18kWh	{31,32,33,34,35,36,37,38,39,40}
37/79	10:00 am – 13:00 pm	24kWh	{35,36,37,38,39,40,41,42,43,44}
38/80	09:00 am – 13:00 pm	6kWh	{1,2,3,4,5,6,7,8,9,10,11,12, 13,14}
39/81	09:00 am – 13:00 pm	<1kWh	{47,48,49,50,51,52,53,54,55,56,57,58,59,60}
40/82	09:00 am – 13:00 pm	12kWh	{15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30}
41/83	09:00 am – 13:00 pm	18kWh	{31,32,33,34,35,36,37,38,39,40}
42/84	09:00 am – 13:00 pm	24kWh	{31,32,33,34,35,36,37,38,39,40,45,46}

[1] The first 42 segments are the price conscious users and the next 42 segments are the time conscious users.
[2] The numbers in brackets correspond to the charging bundles that were defined in Table 6.2.

Appendix E: FCFS Simulation Results

Table E.1: FCFS simulation results at Westfield area, for three demand and three capacity scenarios and Non Locational Pricing

Parking location	Parking Facility One				Parking Facility Two				Total Revenue[1]
Hours starting at:	09:00	10:00	11:00	12:00	09:00	10:00	11:00	12:00	
					Non Locational Pricing (NLP)				
25% EVs, 0% headroom									
Remaining charging posts	421	556	625	513	507	592	625	559	
Remaining power (kW)	1034	1	0	215	419	1	0	49	
Non-allocated vehicles	111	258	300	163	58	136	166	96	
Revenue	549	173	0	317	336	91	0	198	1664, 1034
25% EVs, 10% headroom									
Remaining charging posts	351	251	241	340	464	433	435	464	
Remaining power (kW)	3264	1059	750	2020	1702	597	359	837	
Non-allocated vehicles	0	0	0	0	0	0	0	0	
Revenue	650	924	944	658	414	520	516	395	5021, 2704
25% EVs, 20% headroom									
Remaining charging posts	352	262	254	343	460	428	429	468	
Remaining power (kW)	5787	3642	3265	4535	2827	1754	1621	2131	
Non-allocated vehicles	0	0	0	0	0	0	0	0	
Revenue	634	839	895	645	411	536	518	380	4913, 168
50% EVs, 0% headroom									
Remaining charging posts	352	561	625	484	456	591	625	549	
Remaining power (kW)	464	1	0	4	184	1	0	2	
Non-allocated vehicles	317	601	645	402	183	306	335	232	
Revenue	797	170	0	432	509	99	0	234	2241, 2062
50% EVs, 10% headroom									
Remaining charging posts	104	18	86	141	310	303	343	357	
Remaining power (kW)	1886	1649	1058	783	864	11	2	328	
Non-allocated vehicles	54	121	150	70	14	43	64	45	
Revenue	1365	1601	1388	1273	894	946	812	766	9045, 7923
50% EVs, 20% headroom									
Remaining charging posts	125	23	22	127	284	219	215	281	
Remaining power (kW)	4427	2473	2027	3124	2074	927	787	1315	
Non-allocated vehicles	38	69	67	33	0	0	0	0	
Revenue	1238	1531	1549	1235	899	1144	1154	892	9643, 6209
100% EVs, 0% headroom									
Remaining charging posts	281	556	625	483	437	592	625	549	
Remaining power (kW)	3	1	0	2	3	2	0	4	
Non-allocated vehicles	819	1328	1373	953	474	675	704	565	
Revenue	1057	183	0	437	589	97	0	235	2598, 2595
100% EVs, 10% headroom									
Remaining charging posts	0	14	81	24	197	308	345	308	
Remaining power (kW)	1276	19	1	8	23	2	2	4	
Non-allocated vehicles	507	815	867	546	249	400	418	302	
Revenue	1721	1595	1403	1693	1283	920	804	944	10364, 10068
100% EVs, 20% headroom									
Remaining charging posts	0	0	0	4	37	24	64	83	
Remaining power (kW)	3679	2426	2069	2375	661	2	2	192	
Non-allocated vehicles	452	718	715	444	138	216	242	168	
Revenue	1726	1616	1621	1714	1700	1750	1625	1566	13318, 10910

[1]The two values of this column are respectively: the revenue from selling the charging bundles and the net revenue after subtracting imbalance costs for the remaining power.

Table E.2: FCFS simulation results at Westfield area, for three demand and three capacity scenarios and Locational Pricing

Parking location	**Parking Facility One**				**Parking Facility Two**				**Total Revenue[1]**
Hours starting at:	09:00	10:00	11:00	12:00	09:00	10:00	11:00	12:00	
					Locational Pricing (LP)				
25% EVs, 0% headroom									
Remaining charging posts	476	560	625	530	471	590	625	550	
Remaining power (kW)	1362	1	0	306	212	1	0	1	
Non-allocated vehicles	42	115	157	84	132	265	291	175	
Revenue	472	202	0	309	391	84	0	194	1653, 1317
25% EVs, 10% headroom									
Remaining charging posts	463	427	422	457	368	338	359	380	
Remaining power (kW)	3851	1919	1556	2468	1056	38	1	454	
Non-allocated vehicles	0	0	0	0	17	37	45	22	
Revenue	470	596	605	469	603	701	639	565	4648, 2796
25% EVs, 20% headroom									
Remaining charging posts	469	440	438	471	353	268	268	345	
Remaining power (kW)	6418	4387	4044	5078	2261	1031	860	1551	
Non-allocated vehicles	0	0	0	0	0	0	0	0	
Revenue	442	553	556	427	623	862	854	632	4948, 935
50% EVs, 0% headroom									
Remaining charging posts	382	561	625	491	441	591	625	550	
Remaining power (kW)	726	2	0	53	3	2	0	2	
Non-allocated vehicles	139	292	332	202	355	579	606	420	
Revenue	786	203	0	471	478	84	0	193	2214, 2058
50% EVs, 10% headroom									
Remaining charging posts	256	159	158	246	254	324	358	320	
Remaining power (kW)	2664	702	396	1446	452	2	1	6	
Non-allocated vehicles	1	4	12	7	138	252	267	166	
Revenue	1089	1436	1398	1115	916	740	652	762	8108, 7120
50% EVs, 20% headroom									
Remaining charging posts	298	222	214	292	113	63	88	154	
Remaining power (kW)	5242	3409	3040	4015	1138	50	1	544	
Non-allocated vehicles	0	0	0	0	33	71	85	49	
Revenue	957	1246	1254	963	1221	1392	1322	1123	9478, 6526
100% EVs, 0% headroom									
Remaining charging posts	308	560	625	481	441	592	625	553	
Remaining power (kW)	204	2	0	2	2	1	0	4	
Non-allocated vehicles	381	643	705	512	888	1277	1296	964	
Revenue	1125	212	0	516	481	83	0	189	2605, 2563
100% EVs, 10% headroom									
Remaining charging posts	55	17	88	95	203	315	359	317	
Remaining power (kW)	1660	9	2	521	2	1	2	2	
Non-allocated vehicles	151	255	293	192	605	891	927	677	
Revenue	1799	1933	1695	1669	1073	771	662	768	10371, 9993
100% EVs, 20% headroom									
Remaining charging posts	58	0	0	62	0	29	73	86	
Remaining power (kW)	4099	2350	2030	2854	216	2	1	3	
Non-allocated vehicles	97	169	173	101	446	669	697	503	
Revenue	1833	2014	2003	1801	1588	1498	1378	1359	13474, 11487

[1]The two values of this column are respectively: the revenue from selling the charging bundles and the net revenue after subtracting imbalance costs for the remaining power.

Table E.3: FCFS simulation results at Canary Wharf area, for three demand and three capacity scenarios and Non Locational Pricing

Parking location	Parking Facility One				Parking Facility Two				Total Revenue[1]
Hours starting at:	09:00	10:00	11:00	12:00	09:00	10:00	11:00	12:00	
					Non Locational Pricing (NLP)				
25% EVs, 0% headroom									
Remaining charging posts	350	565	625	585	456	584	625	595	
Remaining power (kW)	766	1	0	3	573	2	0	4	
Non-allocated vehicles	143	338	376	250	92	202	244	180	
Revenue	657	152	0	117	496	114	0	88	1625, 1310
25% EVs, 10% headroom									
Remaining charging posts	299	194	193	312	394	348	355	404	
Remaining power (kW)	3965	1831	1566	2158	3120	1557	1322	1653	
Non-allocated vehicles	0	0	0	0	0	0	0	0	
Revenue	773	1046	1034	729	569	745	704	549	6150, 3043
25% EVs, 20% headroom									
Remaining charging posts	294	182	183	306	394	352	349	402	
Remaining power (kW)	7522	5297	4905	5333	5720	4192	4057	4552	
Non-allocated vehicles	0	0	0	0	0	0	0	0	
Revenue	770	1072	1060	735	578	729	729	554	6226, -1117
50% EVs, 0% headroom									
Remaining charging posts	332	566	625	584	389	585	625	595	
Remaining power (kW)	319	1	0	3	120	2	0	3	
Non-allocated vehicles	426	779	820	582	265	470	495	382	
Revenue	911	155	0	123	765	119	0	92	2164, 2060
50% EVs, 10% headroom									
Remaining charging posts	81	0	0	58	155	73	98	187	
Remaining power (kW)	2762	924	645	738	1813	245	182	412	
Non-allocated vehicles	94	172	178	94	12	31	50	36	
Revenue	1453	1612	1584	1488	1325	1601	1488	1219	11770, 10194
50% EVs, 20% headroom									
Remaining charging posts	86	0	0	76	144	49	52	152	
Remaining power (kW)	6389	4437	4067	4270	4282	2727	2641	2934	
Non-allocated vehicles	86	157	166	89	15	20	27	17	
Revenue	1430	1609	1599	1421	1356	1650	1630	1296	11991, 5679
100% EVs, 0% headroom									
Remaining charging posts	294	567	625	586	365	582	625	594	
Remaining power (kW)	3	2	0	3	3	2	0	3	
Non-allocated vehicles	1039	1646	1657	1208	713	1001	1018	827	
Revenue	1034	149	0	118	829	124	0	94	2347, 2345
100% EVs, 10% headroom									
Remaining charging posts	6	0	0	0	14	8	50	111	
Remaining power (kW)	2175	837	549	228	1076	66	1	3	
Non-allocated vehicles	652	1005	1033	686	344	500	527	407	
Revenue	1723	1601	1595	1676	1794	1769	1645	1450	13253, 12290
100% EVs, 20% headroom									
Remaining charging posts	10	0	0	0	12	0	0	0	
Remaining power (kW)	5545	4278	3958	3558	3782	2729	2538	2100	
Non-allocated vehicles	627	992	1009	655	328	480	493	352	
Revenue	1739	1612	1598	1712	1838	1827	1809	1814	13949, 8236

[1]The two values of this column are respectively: the revenue from selling the charging bundles and the net revenue after subtracting imbalance costs for the remaining power.

Table E.4: FCFS simulation results at Canary Wharf area, for three demand and three capacity scenarios and Locational Pricing

Parking location	Parking Facility One				Parking Facility Two				Total Revenue[1]
Hours starting at:	09:00	10:00	11:00	12:00	09:00	10:00	11:00	12:00	
					Locational Pricing (LP)				
25% EVs, 0% headroom									
Remaining charging posts	471	570	625	584	407	585	625	596	
Remaining power (kW)	1231	2	0	3	310	2	0	3	
Non-allocated vehicles	49	143	187	128	178	385	421	305	
Revenue	526	177	0	141	582	99	0	74	1599, 1319
25% EVs, 10% headroom									
Remaining charging posts	455	419	416	464	254	147	153	267	
Remaining power (kW)	4788	2806	2561	2984	2367	596	347	813	
Non-allocated vehicles	0	0	0	0	0	3	7	3	
Revenue	491	612	613	456	860	1140	1117	816	6104, 4329
25% EVs, 20% headroom									
Remaining charging posts	443	415	413	452	264	148	162	270	
Remaining power (kW)	8072	6172	5885	6473	5161	3319	3143	3352	
Non-allocated vehicles	0	0	0	0	0	0	0	0	
Revenue	497	615	609	473	803	1150	1074	791	5977, -376
50% EVs, 0% headroom									
Remaining charging posts	376	569	625	585	372	582	625	595	
Remaining power (kW)	652	1	0	3	3	2	0	3	
Non-allocated vehicles	152	347	381	294	521	864	882	653	
Revenue	868	182	0	144	685	105	0	77	2061, 1931
50% EVs, 10% headroom									
Remaining charging posts	245	144	128	234	66	58	92	137	
Remaining power (kW)	3757	1651	1248	1721	1021	2	1	3	
Non-allocated vehicles	0	2	5	2	159	275	293	192	
Revenue	1158	1482	1497	1162	1397	1402	1305	1181	10585, 8986
50% EVs, 20% headroom									
Remaining charging posts	258	161	150	252	44	0	0	20	
Remaining power (kW)	7285	5222	4717	5156	3620	2349	2303	2042	
Non-allocated vehicles	0	1	2	1	129	227	236	128	
Revenue	1133	1454	1451	1133	1458	1555	1537	1498	11219, 5697
100% EVs, 0% headroom									
Remaining charging posts	297	569	625	585	367	584	625	595	
Remaining power (kW)	89	1	0	3	4	2	0	3	
Non-allocated vehicles	438	726	770	613	1247	1818	1826	1380	
Revenue	1211	181	0	142	691	104	0	77	2406, 2387
100% EVs, 10% headroom									
Remaining charging posts	45	0	0	9	0	12	64	120	
Remaining power (kW)	2437	845	603	402	946	9	1	4	
Non-allocated vehicles	156	269	287	166	797	1143	1191	884	
Revenue	1899	1981	1956	1940	1584	1518	1378	1226	13483, 12602
100% EVs, 20% headroom									
Remaining charging posts	62	0	0	9	0	0	0	0	
Remaining power (kW)	5968	4240	3945	3680	3614	2656	2431	2041	
Non-allocated vehicles	155	243	261	143	798	1127	1139	817	
Revenue	1835	1983	1953	1950	1592	1547	1540	1535	13935, 9121

[1]The two values of this column are respectively: the revenue from selling the charging bundles and the net revenue after subtracting imbalance costs for the remaining power.

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