MODELLING ELECTRIC VEHICLE USE AND CHARGING BEHAVIOUR

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To my father

Declaration

The research that is presented in this thesis is my own, except where the work of others is referenced.

Abstract

This thesis explores the role of consumers' choices into the integration of mobility and power systems. It will contribute to the wider literature of electric vehicles-power systems integration by explicitly accounting for consumers' preferences in shaping charging demand. This objective is achieved by developing a methodology to investigate electric vehicles (EV) charging choices in technological scenarios that enable smart charging operations.

A modelling framework for the joint analysis of EV charging and activity-travel behaviour is introduced. This is based on an extension of traditional activity scheduling models that embeds the charging choice dimensions: namely the available energy after charging (that is related to the driving range) and the charging duration (defined here as the time elapsed from arrival at a charging facility until the desired battery level is achieved). This framework accommodates the interaction between charging behaviour and travel/activity behaviour, and allows us to capture the potential effects of charging service pricing and charging demand management policies on charging choices as well as along the timing dimension of travel/activity choices.

A stated response survey instrument for estimating a tour-based operational version of the model is developed. Results from this empirical study provide insights into the value placed by individuals on the main attributes of the charging choice. The trade-offs between target battery levels and schedule delays potentially induced by long durations of the charging operation are also analysed.

The model is then implemented into a micro-simulation framework to demonstrate the model applicability for modelling electric vehicle charging demand. The specific application shows the compatibility of charging choices under various electricity pricing scenarios with electric vehicle load flexibility – an essential requirement to enable smart charging operations.

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Chapter 1
INTRODUCTION

1.1 Overview

This initial chapter aims to:

- Introduce the drivers for electrification of road transport;
- Describe the system components involved;
- Justify the need to model such a system and in particular electric vehicle use and charging patterns;
- Introduce the motivation for this thesis and explain how it is structured.

1.2 Drivers of mobility electrification

Transport is one of the fundamental components of the globalised economy, allowing the circulation of goods and people and the associated social exchanges. Moreover, by reducing the constraints on individuals' movement, it is also associated with the universal value of freedom. In most countries, including the UK, road transport remains the dominant mode of transport. Indeed, passenger cars can be considered as emblematic of mobility freedom, since they (ideally) provide individuals with the greatest degree of independence and flexibility.

Governments around the world, however, are committed to reducing reliance on foreign energy imports; to decarbonise society in an effort to limit human induced climate change; to improve the air quality in cities and generally increase the sustainability of urban environments given the rate of increase in urbanisation.

IEA (2009b) forecasted that by 2025 world energy consumption would increase by 50% from the 15 billion tons of oil equivalents in 2015. It is evident that emerging economies (e.g.

China, India, Latin America and the Middle East) are now taking over as the main drivers of global energy demand (IEA, 2013b). While the United States is headed towards meeting its energy needs by 2035[1] by exploiting domestic resources, European countries are under pressure by this increase in energy consumption in other parts of the world due to their reliance on foreign imports of fossil fuels. In Europe, therefore, energy security is likely to be the most important motivation for a strong reduction in the reliance on oil for road transport, especially given that this sector accounts for 78% of all European oil consumption (ERTRAC et al., 2012). The UK is no exception to these pressures and risks coming from global energy markets due to dependence on foreign imports.

Road vehicles dominate global CO_2 emissions from transport. In 2008 the transport sector contributed 22% of global CO_2 emissions from fuel combustion, with road transport comprising 73% of global transport emissions, amounting to 4.5 Gt of CO_2. This percentage rises to 92% for the UK in 2008, (IEA, 2010). Passenger cars constitute the bulk of the climate impact from road transport in the UK: in 2007 they generated 58% of the total domestic transport greenhouse gases (GHGs) emissions, (DfT, 2009).

It is argued that electrification of road transport "has great potential to significantly reduce the consumption of petroleum and other high CO_2-emitting transportation fuels" (IEA, 2009a), and that this will serve to reduce the climate impact of road traffic, provided that the electricity sector itself is progressively decarbonised. An additional benefit from the deployment of electric vehicles in urban areas is that it will contribute to an increase in local air quality given the null (or potentially very low, for plug-in hybrid electric vehicles) tailpipe emissions.

Based on the above motivations the UK government has taken action to accelerate the market uptake of electric vehicles and "ultra low carbon vehicles" (ULEV) in general, with a vision to virtually decarbonise the UK fleet by 2050. In particular, an initial provision of £400 million to 2015 was invested into:

- Purchase support for ULEV, mainly through car and van grants aimed at reducing the cost gap between conventional vehicles and ULEVs; provision of electric vehicle infrastructure.

[1] According to (IEA, 2013b).

- Research and development, and reduction of emissions from vehicles other than passenger cars or vans (e.g. buses for urban public transport).

This commitment is set to continue between 2015 and 2020, with a further provision of over £500 million (OLEV, 2013).

A further driver for transport electrification, underlying the considerable government support for ULEVs programmes, is the desire to foster the domestic supply chain industry that should benefit from a future decarbonised mobility mass market (OLEV, 2013).

1.3 Electric vehicle technology

Electric drive technology has been part of the automotive industry since the beginning of its history. Before the internal combustion engine technology had won the competition with other technologies, a consistent share of the first motor vehicles produced was based on electric drive. Famous examples of the first generation of electric drive vehicles are Mrs. Ford's own car (Sperling and Gordon, 2008), or the 1902 Lohner-Porsche, the first hybrid electric vehicle (van Vliet et al., 2010).

Electric drive vehicles, (EDV) often referred to simply as electric vehicles, are road vehicles involving electric propulsion, (Chan and Wong, 2004). This encompasses battery electric vehicles (BEV), hybrid electric vehicles (HEV), fuel cell vehicles (FCV) (Chan and Wong, 2004, Sperling and Gordon, 2008), and also combinations of these technologies, such as plug-in hybrid electric vehicles (PHEV) (Chan, 2007), and plug-in fuel cell vehicles (PFCV) (Thomas, 2009, Offer et al., 2010). These electric drive vehicle technologies differ from each other based on how the electricity for vehicle propulsion is generated and stored.

This thesis focuses on battery electric vehicles, although some consideration will also be given to PHEV since they are both "plug in" vehicles, i.e. they draw electric power from the grid to charge on-board battery packs storing electric energy for propulsion.

The purpose of this section is to give a brief overview of BEV/PHEV technology and the infrastructural requirements for their deployment. The focus is especially on the technological issues affecting adoption and use behaviour and on the infrastructure related issues that can be addressed by appropriate demand modelling.

Before continuing with the subject of this section a lexical note is given. Because the focus of this research is battery electric vehicles, in the rest of the report the general term electric vehicles is used to indicate BEVs, unless it is specified otherwise. The two acronyms BEV and EV will be used interchangeably.

1.3.1 Vehicles architectures

In all types of EDVs, all or part of the propulsive energy is electricity that is converted into mechanical energy to drive the wheels by one or more electric motors. Thus, the electric motor is a common component of all the EDV types mentioned above.

In battery electric vehicles electric motors convert the electric power drawn from the battery into the mechanical power that drives the wheels. No electricity generation occurs on board; the electricity is generated externally and charged into the batteries that store it electrochemically. BEVs' batteries are typically charged by connecting them to the electricity distribution grid. The propulsive system is very simple consisting only of batteries, power electronics and motors. In BEVs a transmission system is not (strictly) necessary, as the motors can drive the wheels directly.

In contrast, plug-in hybrid electric vehicles (PHEV) do not rely only on grid electricity for their propulsion. In effect they are HEVs in which *part* of the energy that is used for vehicle propulsion is generated on-board with the remaining part being drawn from the grid by connecting ("plugging-in") the vehicle to an electrical outlet, when it is parked. This externally generated electricity is stored electrochemically into batteries, as in battery electric vehicles. The rest of the propulsive energy is generated on board by an internal combustion engine (ICE). PHEVs, like HEVs, can exist in different architectures that are classified in term of the flows of the propulsive power. Parallel hybrids present the ICE and the electric motor operating on the same shaft, providing power to the wheel separately or simultaneously. In series hybrids no mechanical connection exists between the ICE and the wheel; the electric motor drives the wheels using power from a battery or the ICE, which works as a power generation unit. A series-parallel hybrid can work in both modes.

PHEV operation is divided into charge depleting mode (CD) and charge sustaining mode (CS). In CD mode the externally generated electricity is drawn from the battery to provide propulsive energy, while in CS mode part of the electricity generated on board by the ICE is used to keep the state of charge of the battery around a certain level, i.e. in CS mode a PHEV operates as a conventional HEV. Depending on the architecture and on the control strategy in CD mode the electric motor can be the only driving unit: in this case the CD operation is defined as "all-electric." In contrast, if the ICE provides propulsive energy while the battery is being discharged, then the CD operation is defined as "blended", because the grid generated electric energy "is blended" with the chemical energy of the conventional fuel. PHEVs working in CD operation as all-electric and CS operation working as pure series hybrid, in which the internal combustion engine does not drive wheels but only works as generator, are often called extended range electric vehicles (EREV). Similar operating concepts to those of PHEVs can also be applied to plug-in fuel cell vehicles, i.e. FCVs with additional batteries that can be externally charged.

For BEVs, PHEVs and ERERVs, recuperation of energy from breaking is enabled: this slows battery depletion.

Collectively BEVs, EREVs and PHEVs are sometimes referred to as plug-in electric vehicles (PEV), to highlight the fact that these are EDV, drawing the entirety, or part of, their propulsive energy from grid electricity.

1.3.2 Energy storage

At the heart of PEV technology there is the energy storage system (ESS). The main storage solution currently being considered for plug-in vehicles is the battery. More specifically, a battery storage system which is called a battery pack: a group of battery modules electrically connected, with the entire pack powering the electric drive system. Each module is a "single mechanical and electrical unit" constituted of connected battery cells, the basic electricity generator unit (Dhameja, 2002). Its constituents are: anode and cathode, separator, terminals, electrolyte and a case. It is beyond the scope of the present report to give a complete description of the physical operation of the battery, however. Dhameja (2002) describes a battery as an electrochemical cell in which voltage is generated by the difference in potential between the electrodes. If the battery terminals are connected to an electric load (e.g. a motor), the circuit is closed and the current can flow through the motor to generate torque, passing from the positive terminal of the battery to the negative terminal. As the process continues the battery provides its stored energy, depleting its charge. Eventually, the battery will pass from a charged to a discharged state. When the terminals are connected to an electric power source, instead of a load, the battery can be charged and the electrodes can be brought back to their original chemical states, i.e. the battery can be fully charged. Partial re-charge is also possible. The battery level at a given level of charge is denominated as the State of Charge, (SOC) (Dhameja, 2002).

BATTERY CHOICE FOR PLUG–IN VEHICLES

The battery selection for plug-in vehicles depends on several factors which include: energy storage requirements; peak power requirements; overall dimension constraints; cycle/calendar life requirements; safety; and both initial and lifecycle costs (Burke, 2009). These factors have major implications for EV adoption, use and charging choices from the consumer behaviour perspective affecting EV adoption. For example, energy storage affects the maximum range an electric vehicle can achieve, while the peak power determines the acceleration. Limited range, acceleration and costs are each vehicle attributes that several studies[2] have shown to significantly affect purchasing choices regarding electric vehicles.

Following Young et al. (2013), Table 1 shows some of the goals in battery parameters that were set out by the USABC[3] consortium for both the mid and long terms, which are intended (in the long term) to make EVs competitive with conventional vehicles. The table also shows their relationship with vehicle attributes important in purchase choices.

Table 1 USBAC Goals, reproduced from (Young et al., 2013),

	Midterm goal	**Long term goal**	**Impact on vehicle's performance**
Specific energy (Wh/kg)	150	200	Range and size
Energy density (Wh/l)	230	300	Range and weight
Specific discharge power (W/kg)	300	400	Acceleration and weight
Discharge power density (W/l)	460	600	Acceleration and size
Specific regenerative power (W/kg)	250	200	Energy saving and weight
Regenerative power (W/l)	230	300	Energy saving and size
Life (years)	10	10	Lifecycle cost
Life cycles	1,000	1,000	Lifecycle cost
Operation temperature (deg C)	−40 to 50	−40 to 85	Life of battery
Selling price ($/kWh) (*)	150	100	Acquisition and replacement costs

(*) This goal appears still unattainable. (IEA, 2012) estimates the current unit cost of about 500 $/kWh and claims that the trend is in line with the goal of reaching 325 kWh by 2020 or less, which IEA deems sufficiently low to bring electric vehicles close to cost-competitiveness with vehicles with internal combustion engine.

Amongst the battery parameters in Table 1 specific energy and specific power are particularly interesting. The first is related to range and size, the second to acceleration and size. A particular characteristic of electrochemical storage technology is that there is a trade-off between these two parameters: to achieve long ranges the battery needs also to increase size and weight so as to attain the required acceleration performances. The plot in Figure 1, called Rangone Plot (Ragone, 1968), shows the trade-off between specific energy and specific power and highlights how the best performances are achieved by batteries based on Lithium-Ion (Li-ion) chemistries.

2 These are reviewed in the next chapter

3 The United States Advanced Battery Consortium LLC (USABC), is a collaborative organization operated by Chrysler, Ford and General Motors, seeking "to promote long-term R&D within the [US] domestic electrochemical energy storage (EES) industry and to maintain a consortium that engages automobile manufacturers, EES manufacturers, the National Laboratories, universities, and other key stakeholders" (USABC)

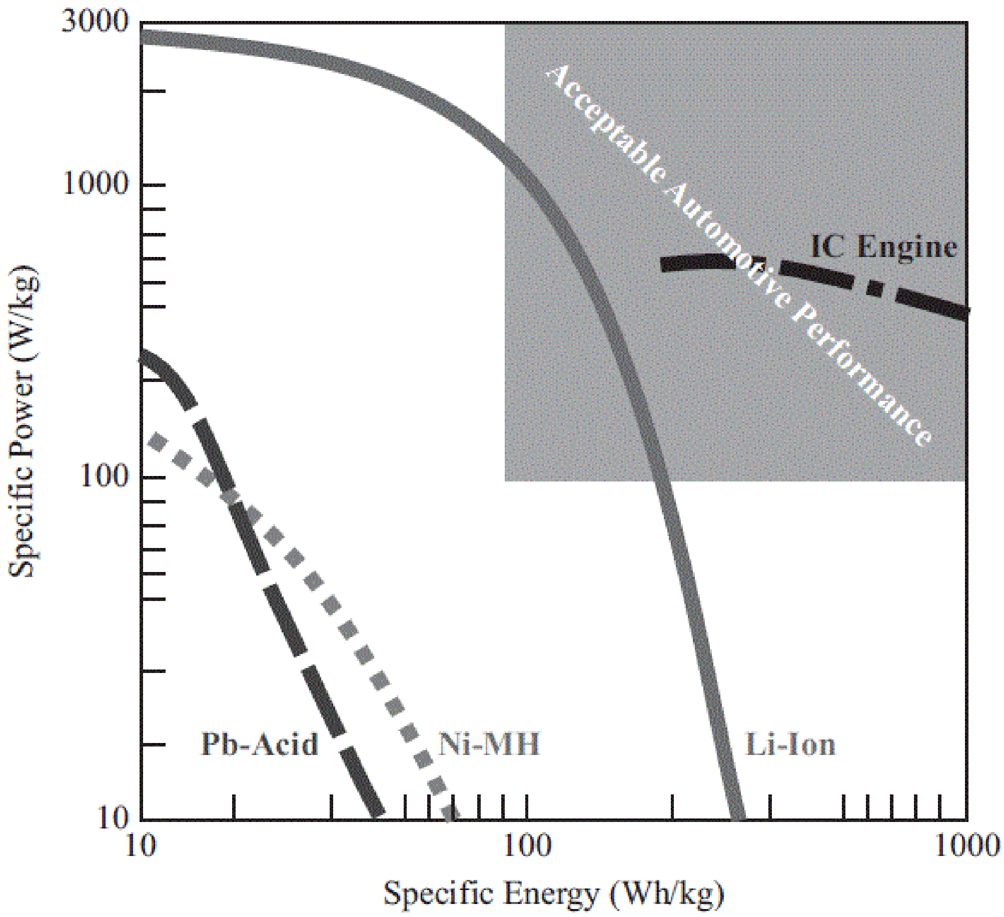

Figure 1: The Rangone Plot for various battery chemistries. It shows the trade-off existing between specific power and specific energy. Reproduced from (Rahn and Wang, 2013). This image has been reproduced with the permission of the rights holder, John Wiley & Sons Ltd.

Although Li-ion batteries show improved specific energy compared to lead acid and Nickel Metal Hydrides (Ni-MH) batteries (typically used in HEVs), they still present both energy density and specific energy limitations with respect to conventional fuels. An indication of the difference is provided in Figure 2, where a comparison of fuel characteristics is presented. The large gap between Li-ion batteries and petrol or diesel is evident.

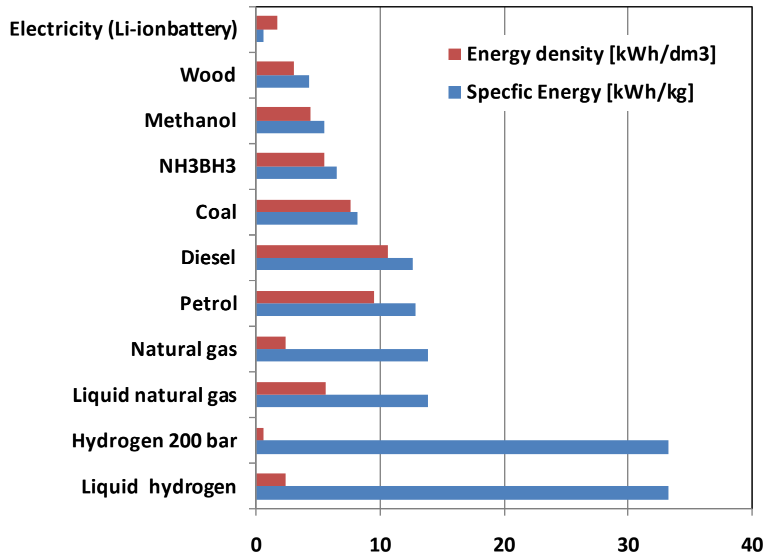

Figure 2: Energy density in [kWh/dm^3] and specific energy [kWh/kg] for various fuels. Container mass and volume are excluded. Data from Edwards et al. (2008).

Clearly the high costs per unit of battery capacity, together with the size issue, impose limitations on the maximum range of electric vehicles currently on the market. This is one of the most discussed market barriers to BEVs (IEA, 2013a), although, for obvious reasons, it does not apply to PHEVs. The limited range of BEVs also affects electric vehicle use and charging behaviour, as well as purchase choices, however, as will be discussed further in Chapter 3. In fact, there is evidence that usage and charging decisions may be affected by a phenomenon often termed "range anxiety", i.e. the fear of not completing a journey due to battery depletion.

1.3.3 The charging infrastructure

The base technology allowing the connection between the vehicle's battery and the grid is simple. A device called a charger is a current rectifier that transforms the grid's AC into DC to be fed into the battery. The charger can be installed on board or installed at fixed points where charging takes place. The on-board solution reduces the complexity of charging infrastructures and allows the user to plug directly into any standard outlet. At public charging locations a charging controller/metering system is also necessary to measure the electricity being drawn the grid for billing purposes.

More complex systems for user/vehicle/charging infrastructure communication are being developed in order to provide particular billing services or to allow *smart charging* operations. The phrase smart charging refers to a charging demand management system that enables the load from electric vehicles to be managed in such a way that grid operations are protected and enhanced, while synergistically meeting the charging requirements necessary to satisfy EV users' driving needs.

Charging points, or electric vehicle supply equipment (EVSE) are generally classified based on charging times for a typical EV (standard/slow, fast and rapid), and by the charging mode, i.e. the technical details of the charging equipment. Table 1 shows how these two classifications are related. Modes 1 and 2 use a standard non-dedicated circuit and socket-outlet, but mode 2 uses a special cable that incorporates a control box for residual current device protection (mode 1 charging is possible, but not suitable for safety reasons). Mode 3, for fast charging, uses a fixed and dedicated outlet. Mode 4, for rapid charging, make use of a dedicated external charger that supplies DC to the vehicle's battery (BEAMA, 2012).

Table 2 Classification of charging facilities

Type	**Time to fully charge a 24 kWh BEV**	**Charging mode**
Slow or standard	~6 to ~10 hours	Mode 2,3
Fast	~1 to ~3 hours	Mode 3
Rapid	~15 to ~30 minutes	Mode 4

From the user perspective, EV recharging is a simple but time consuming operation. Indeed standard charging is most suitable for overnight recharging, (or in general for situations in which the vehicles are parked for long hours at the same location). Even overnight recharging, however, requires the availability of a socket at the location where the vehicle is parked. Figure 3 shows the distribution of locations where the vehicles are parked overnight in Great Britain, by area type. A large proportion of vehicles in urban areas are parked on the street. This is one of the reasons why the development of an on-street recharging infrastructure is required (GLA, 2009)

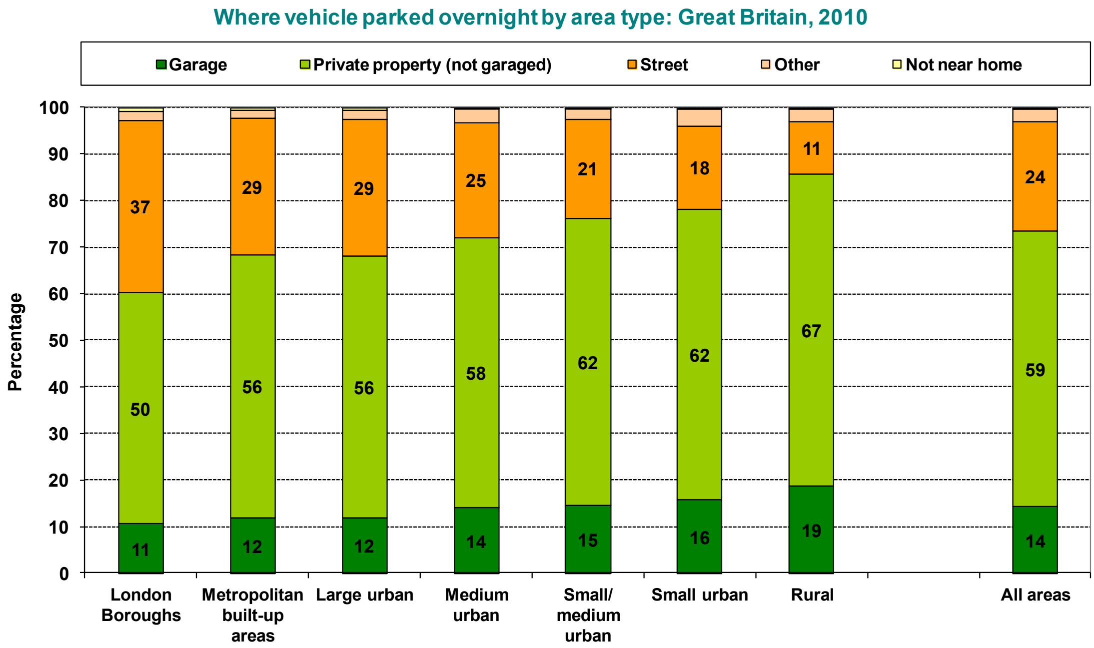

Figure 3 Location of overnight parking in Great Britain. Reproduced from the National Travel Survey 2010 webpage (DfT, 2011), under the Open Government Licence v2.0 (TNA, 2012)

It is worth noting here that deployment of slow public charging facilities is controversial. They do not improve the mobility flexibility of EVs, and EV trials around the world have shown that users tend to neglect public charging points, unless they allow fast charging (Golob and Gould, 1998, Slater et al., 2009, Becker, 2010). On the other hand deployment of a public charging infrastructure in residential area can potentially avoid the situation where electric vehicle adoption self-selects those individuals who have the possibility to charge at private premises, excluding potential adopters who only have access to on-street parking.

Public fast/rapid charging facilities have the benefit of supporting long-range drives and also serve as a means to mitigate range anxiety, however it has been argued that their operation are only profitable when EV penetrations rate are already high (Schroeder and Traber, 2012). Consequently, their deployment by private investors at low penetrations levels must be subsidised or driven by other prospects than profiting from EV recharging.

1.4 Electric vehicle's integration into power systems

From the perspective of the power systems, plug-in electric vehicles represent both a challenge and a potential opportunity. On the one hand, a large penetration of PEVs can impact power systems, especially at the distribution network level, and requires implementation of effective load management strategies (Heydt, 1983). On the other, it has been recognised that PEVs can also represent a resource to power systems, especially if the latter are characterized by large shares of intermittent or fluctuating renewable energy sources (RES) (Kempton and Letendre, 1997, Kempton and Tomić, 2005).

If grid connected EVs are treated as inflexible loads, then charging operations carried out without any type of control (from external entities, from on-board computers or EV users themselves, using information provided by distribution network operators) can compromise the operation of the distribution network assets (see for example Strbac et al. (2010)). If instead the potential flexibility of PEVs loads is exploited, then it is possible both to manage the charging load to avoid a critical situation for grid operations and actually to use PEVs for services to the grid.

Bessa and Matos (2012a) and Galus et al. (2012a) provide reviews of studies that have considered the potential of PEVs for grid services. These encompass reduction of system costs by exploiting the temporal flexibility of the PEV charging load; ancillary services such as frequency regulation and storage and backup power of intermittent renewable energy. Some of these such potential services, such as downward frequency regulation, treat PEVs purely as controllable loads, others, instead, require equipment that allows bidirectional power flows between vehicles and the grid to enable so called V2G (vehicle-to-grid) operations. For example, to balance renewable energy sources, PEVs draw energy from the grid when RES are producing more than forecasted, while feeding power into the grid system (drawing from the available energy in their batteries) when production from RES falls short of forecasts.

The type EV-grid operations described above can be enabled within the broader paradigm of smart grids where distributed and renewable generators, the use of storage devices and demand side participation are integrated by means of advanced communication and control systems.

In the energy systems literature two alternative frameworks have been devised for the inclusion of electric vehicles into smart grids: an aggregator-based framework and a concept based on decentralised control architecture (Galus et al., 2012a).

The first concept is based on an entity called an aggregator, which serves as an intermediator between vehicle owners and the utility. This framework assumes that electric vehicle owners cannot, as individual entities, have transactions with the electrical utilities nor bid in the electricity market due to the low power transactions they represent (Bessa and Matos, 2012a). According to Bessa and Matos (2012a), (Kempton et al., 2001) first introduced the idea of the

EV aggregator as an intermediary entity for V2G operations. EV aggregators have also been considered as pure load aggregators controlling the charging operations of a fleet of member electric vehicles. The typical aggregator based approach to charging demand management implies direct control. This means that control actions are imposed on electric vehicles without the involvement of the electric vehicle owners (Galus et al., 2012a). Such actions must, however, respect the constraints imposed by owners' travel needs. This means that the aggregator must collect charging requirements from each member vehicle. Sundstrom and Binding (2011) formalise the requirements that EV users communicate to the aggregator in terms of an energy requirement and a timing requirement. The first is the battery level required by the end of the charging operation, the second is the time by which the charging operation must be completed.

Users, through their charging requirement preferences, affect the flexibility of the controls that can be imposed on the charging operation. On the other hand, depending on how the charging service is contracted by the aggregator (for this reason sometimes called the charging service provider), those user requirements allowing flexibility may be contracted while charging requirements implying an inflexible load may be dissuaded by pricing. Contracts regulating the charging for service provision may also include the possibility for users, at a premium, to override the charging control imposed by the aggregator and charge continuously at the maximum charging power allowed by the charging facility in specific situations that may require vehicle availability in shorter times (Sundstrom and Binding, 2011).

In the decentralised concept individual EVs optimize their charging based on the market information made available to them. Typically a price signal is used to incentivise a particular charging behaviour (Galus et al., 2012a). Price signals may be static or dynamic. An example of static price signals are time of use tariffs that would incentivise charging overnight, similar to current time of use domestic tariffs for electricity. Note that, even in a decentralised framework, an aggregator entity might provide these pricing signals to owners of electric vehicles (Galus et al., 2012a).

In this perspective the centralised aggregator-based approach and the decentralised approach somehow meet and are differentiated only by whether the charging control systems optimise the charging operations of a group of vehicles or minimise the charging cost of a single vehicle. In the first case, the operational management algorithm of the aggregator minimises a cost function using information on the requirements of member vehicles, market prices and distribution network constraints. In the second case, the control system on a vehicle minimises the costs of the charging operation for a single vehicle subject to the user requirements and the price signals coming from an aggregator. In turn, the latter generates these signals as a result of information from connected member vehicles, grid constraints and market prices.

Depending on the level of involvement of EV users in the control of the charging operation, smart charging can be interpreted as a form of demand side management (DSM) or demand response (DR). Both DSM and DR are based on the idea of exploiting flexibility of demand; however, while the first approach traditionally implies “activities centrally coordinated by electric vehicle utilities”, the second is different in that it relies on “voluntary and independent decentralised decision making by suppliers and customers” (IEA, 2011). Given that users’ involvement in smart charging is not a binary variable, but one that changes gradually between a small level in the direct control aggregator based approach and a large degree in the decentralised paradigm, the distinction between DSM and DR is actually somewhat blurred.

1.5 Demand models for EV impacts assessment

The factors driving the shift towards electric mobility as well as the challenges posed by this shift to the power systems collectively represent the expected impacts of electric vehicle deployment. The impact areas mentioned in the previous sections are energy security, climate change, air pollution, economic spinoffs, and impacts on power systems. Further economic impacts derive from changes in the way the power systems are operated in the presence of electric vehicles as well as changes in private personal mobility due to changes in the price of fuel (and thus the cost per mile of driving).

Given the still low penetration of electric cars in national fleets such impacts are mainly accessed via mathematical models, which in turn require models of:

- Electric vehicle demand for market share forecasting;
- Usage and charging demand patterns.

The extensive exploration vehicle demand modelling has lead enabling increasingly realistic representations adoption behaviour. Instead, models of electric vehicle use and charging patterns need further development, because despite the plethora of publications that are currently being published on analyses of potential EV impacts, the representation of EV use and adoption behaviour still relies on strong assumptions.

A review of electric vehicle use and charging demand modelling is carried out in the next chapter. This necessarily includes a review of EV adoption, as adoption and use are often modelled jointly for impacts assessment of electric vehicle usage and charging patterns.

The review identifies the simplistic way charging behaviour is treated in models for impact analysis (typically, separately from travel behaviour) as an important gap in the current state of knowledge. Indeed, the review will show that most impact analyses are based on predetermined charging behaviour scenarios and travel patterns. This use of predetermined data fails to capture interactions between charging patterns and travel patterns activated by policy actions aimed at managing charging demand,

The review will also highlight modelling frameworks that adopt a more holistic approach by explicitly modelling both charging behaviour and travel patterns, potentially allow the capture of synergy and conflicts between, for example, power system policies and travel behaviour. It will argue, however, that a deeper understanding of the intertwined travel and charging decisions of electric vehicle drivers is needed to inform any improvement in these models. This is deemed particularly important when smart charging operations are involved, since EV users' behaviour is paramount for the determination of the effectiveness of demand response strategies.

1.6 Thesis objectives and structure

Motivated by the need, identified in the review in the next chapter, to improve the modelling of charging behaviour for EV use and charging demand modelling, this thesis explores the role of consumer choices in the integration of mobility and power systems. It will contribute to the wider literature on the integration of electric vehicles and power systems by explicitly accounting for consumers' preferences in shaping charging demand. This objective is achieved by developing a methodology to investigate EV charging choices in technological scenarios that enable smart charging operations.

Thus, the overall aim of this thesis is to improve the electric vehicle use and charging models to achieve more realistic charging patterns also in response to DSM/DR and improve the realism in impact analyses. The specific objectives are:

- To analyse electric vehicle use and charging choices jointly in response to price-based DSM/DR measures. Specifically, a modelling framework for electric vehicle use scheduling and charging decisions is developed.
- To explore preferences in charging operation attributes and EV use timing and their heterogeneity across drivers.

- To demonstrate the use in the modelling framework to simulate the effect of user preferences on the effective deployment of DR/DSM measures.

The first objective is achieved by extending the traditional modelling framework for time of day choices used in travel demand literature to embed charging decisions.

The second objective is achieved by:

- Developing stated choice experiments in which electric that capture tradeoffs between charging option attributes and activity-travel timing;
- Using discrete choice methods to analyses choice experiments' data.

The third objective is achieved by implementing a simulation framework to study the flexibility of electric vehicle load, enable by EV use scheduling and charging preferences under various, electricity tariff scenarios.

The thesis is structured as follows:

Chapter 2 provides a review of the literature on electric vehicle use demand modelling. Modelling methodologies are classified and limitations identified in the way charging behaviour is treated. Although Chapter 2 is a literature review chapter, the review of the literature that is relevant to this thesis is not only contained within this chapter. Other chapters of the thesis also contain literature reviews parts useful for the specific purposes of the specific chapters.

Chapter 3 first reviews the literature available on charging behaviour and introduces a conceptual model of charging choice. It then introduces a modelling framework for the joint analysis of EV charging and activity-travel choices. In particular, the model extends a traditional activity-travel scheduling choice modelling framework by embedding charging choice dimensions within it. Chapter 3 also includes a brief review of activity-travel timing choice models, as this is relevant to the development of the extended modelling framework.

Chapter 4 extends the analysis of the stated response methods discussed in chapter 2 to motivate the design of the data collection tool to collect EV use scheduling and charging data suitable for estimating the parameters of a random-utility model for charging and activity-travel timing choices. The chapter then presents the features of ECarSim, the survey tool finally developed.

Chapter 5 gives a brief overview of the specific discrete choice models used in the subsequent analysing the choice experiment data, and then shows the results from the estimation of discrete choice models based on the two stated choice experiments part of ECarSim. These provide insights into the value placed by individuals on the main attributes of the charging choice and how these are traded off against the timing characteristics schedule delays potentially induced by long charging durations.

Chapter 6 describes the implementation of a simplified version of the model developed in Chapter 3, estimated using data jointly from the two choice experiments in ECarSim in a micro-simulation framework. This is used to demonstrate the applicability of the model for modelling electric vehicle charging demand. The specific application shows the compatibility of charging choices under various electricity pricing scenarios with electric vehicle load flexibility – an essential requirement to enable smart charging operations.

Chapter 7 provides a summary of the research reported in the previous chapters, highlighting the main conclusions and original contributions. Suggestions for further work aimed at further improving EV use and charging behaviour modelling are also provided, in light of the limitations that this research bears.

Chapter 2
ELECTRIC VEHICLE USE DEMAND MODELLING LITERATURE

2.1 Overview e purpose of the chapter

This chapter discusses the modelling approaches that have been adopted in electric vehicle (EV) demand modelling, by reviewing a number of representative studies. Strengths and weaknesses are highlighted with respect to the particular analytical aspect of interest in terms of EV-grid integration and the chapter goes on to use this assessment to identify the gaps between the best current approaches and the comprehensive demand model system required in integrated personal mobility/power system scenarios. Some of the research requirements identified in this chapter are addressed in the following chapters, constituting the core contribution of this dissertation.

Therefore the purpose of this chapter is to motivate the need of improving the way electric vehicle use and charging behaviour is modelled within demand model systems, and ultimately provide a motivation for the development of the conceptual modelling framework developed in Chapter 3.

It is reiterated that the reviews of the literature that is useful for the purposes of this thesis is not limited to the present chapter. The review presented here is intended to identify the issues in modelling electric vehicle use and charging demand. Other chapters of the thesis also contain literature reviews parts useful for the specific purposes of the specific chapters. Specifically:

Chapter 3 reviews the literature available on charging behaviour and includes a brief review of activity-travel timing choice models, as this is relevant to the development of the extended modelling framework.

Chapter 4 extends the analysis of the stated response methods discussed in the present chapter (section 2.3.1) to motivate the design of the data collection tool developed for thesis.

Chapter 5 gives a brief overview of specific discrete choice models that are used in the analysis of choice experiment data that follows. Note that discrete choice models are introduced already in the present chapter (section 2.3.1), in the context of EV adoption models.

2.2 A classification of EV use demand modelling approaches

The integration of transport and power networks required by the introduction of personal electric mobility is expected to have effects encompassing the different impact areas described in the previous chapter. The magnitude of the impacts and the strategies for their mitigation (when negative) or promotion (when positive) are in most cases estimated and analysed by making use of mathematical models. There are two reasons for this. Firstly, data about electric vehicle (EV) use is scarce due to the low adoption levels to date. Secondly, and most importantly, even when data is available, models need to be developed to assess impacts in conditions that do not necessarily coincide with those described by the available data.

Mathematical models are very powerful in exploring such nascent markets. In fact, some analyses have recently been carried out using real world data from electric vehicle trials. For example, the work carried out by Robinson et al. (2013) estimating the impact of CO_2 emissions from real world charging profiles, or that of Bruce et al. (2012) and Schey et al. (2012), who observe the effect of monetary incentives and pricing on the time of charging. In most cases, however, despite offering invaluable insights into the characterisation of electric vehicle use and behaviour, these types of studies only provide descriptive results,[4] whereas

[4] A few recent real world charging patterns analyses that go beyond descriptive statistics will be discussed in more detail in the next chapter (Franke and Krems 2013, Zoepf et al 2013), where recent literature in charging behaviour analyses is reviewed in detail before the introduction of the modelling

the rapidly evolving context of transport electrification requires policy sensitive tools that are sufficiently flexible to enable investment decisions in a rapidly changing landscape. Furthermore, analyses are required to anticipate future electric vehicle deployment scenarios, so that policies managing such impacts can be designed and, if the modelling systems allow it, tested.

Richardson (2013) has classified the models used in analysing integrated EV-grid systems into two broad categories: long term models for system scale planning and hourly time series models. This classification, although valid insofar as it identifies the two timescales that characterise the purposes of the analyses, does not take into account other important distinctions. In particular, hourly time series models have methodological differences that reflect their different purposes. For example, both emission analyses and impact analyses on the distribution network require time of day power profiles to be generated ("hourly time series"). The former because the marginal emission factor of a grid system depends on the time of day (Hawkes, 2010), and the latter because electric vehicle load on the grid is time dependent (since it is the result of the joint effect of potentially time dependent electricity pricing and time dependent mobility needs) and because it is additional to an existing time dependent domestic load, potentially leading to congestion at the network bottlenecks. Emission analyses and distribution network impact analyses, however, do not require the same level of spatial disaggregation.[5] Information from disaggregate models can then be aggregated to the required level using techniques that do not require arbitrary assumptions, allowing emission analyses to be carried out using disaggregate models. On the contrary, using top-down approaches to assign information to specific segments of the population that has been modelled at an aggregate level requires the adoption of assumptions regarding how this information is distributed amongst the segments. Coming back to the example of the impact analysis from EV charging on the distribution network, spatially distributing a

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framework for charging behaviour developed in this thesis. The present chapter is mainly devoted to the review of the modelling approaches adopted to analyse electric vehicle deployment impacts.

[5] In a grid system in which the level of self-generation, and decentralised generation in general, is not negligible it may be of interest to also analyse emissions from electric vehicle charging at a spatially disaggregate level.

regional level electric vehicle load over the network requires assumptions regarding the distribution of vehicles and their characteristics as well as their usage patterns[6].

In this chapter EV use analyses are classified based on the timescale for which electric vehicle use is modelled, as well as on the level of aggregation usage and energy cosumption metrics that are modelled. The following model classes are therefore considered:

- Car ownership and vehicle use models. Vehicle holdings are typically modelled at the household level; vehicle use is typically at vehicle level using annual mileage as the metric. Because vehicle use is modelled on an annual timescale, we classify them as long-period models.
- Short period models. The metrics of vehicle use and energy consumption are modelled on a time scale of the order of the hour (or fraction of hour). The spatial/physical scale at which the relevant usage metrics are modelled varies from aggregated regional levels to the atomic vehicle/individual level.
    - Regional-level models: hourly demand profiles are estimated aggregately over a regional fleet;
    - Vehicle/driver-level models. These are agent-based models: hourly demand profiles are modelled for each vehicle (or driver) agent. Depending on how each vehicle pattern is generated we further classify them as:
        - Trip-based (the trip is the fundamental travel pattern unit)
        - Activity-based (coherent chains of activities and trips, i.e. schedules constitute the (activity-)travel pattern unit;
        - Vehicle state Markov Chain models (the pattern unit is typically the vehicle state, e.g. driving/parked.

[6] Issues involving transfer information from small scale data (e.g. disaggregate in space/time) to large scale data (e.g. aggregate in space time), and *vice-versa* are often encountered in hydrology, where the prediction space/time scales may be different from those characterising the data or the model outputs. Methodologies to enable this cross-scale transfer of information (upscaling and downscaling methods) are the subject of a large body of hydrology literature and environmental sciences. The review of such methods is far beyond the scope of the present chapter; however we the existence of approaches that may be helpful in addressing the downscaling/upscaling issues identified in the context of EV impact analyses. For a review the reader is deferred to (Bierkens et al., 2000)

A graphical summary of this classification is shown in Figure 4. Model classes are presented by rectangular boxes, ordered hierarchically along the vertical dimension of the graph. References to studies adopting approaches belonging to specific classes hang from the lowest class box.

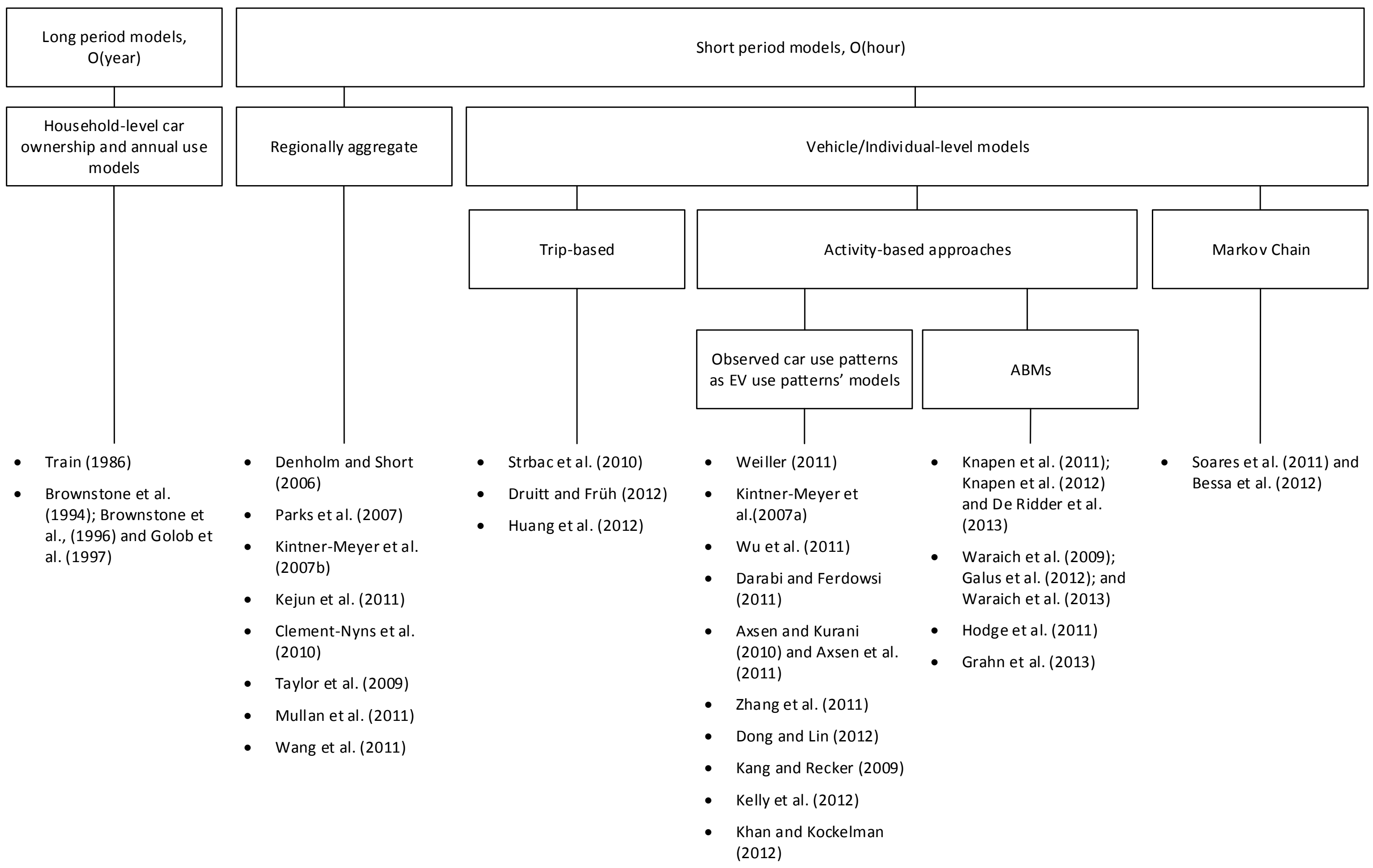

Figure 4 Classification structure for models of electric vehicle use

2.3 Vehicle ownership and annual mileage models

The most investigated aspect of electric vehicles in transport demand literature is without doubt adoption. Adoption models have mostly been used to understand how to foster electric vehicle demand, specifically to identify the main drivers and barriers that determine demand and to policy test incentive strategies. They can also be used, however, to forecast electric vehicle penetration and prioritise infrastructure investments, since the allocation of resources requires reliable estimates of market penetration so that the risk of resource waste on unlikely system states is minimised.

For example, investments in public charging infrastructure deployment can be viewed on the one hand as a strategy to incentivise electric vehicle adoption. On the other hand, the infrastructure location is not irrelevant for the effectiveness of these policy measures, which need therefore to be planned carefully. These two aspects can be jointly analysed with appropriate vehicle ownership models, provided that the model can account for spatial heterogeneity in car buying households. For instance spatial heterogeneity in the availability of private parking spaces (driveways and garages) and in income may have important effects, regarding how to direct investments incentivising electric vehicle uptake. In some areas, reducing the charging infrastructure barrier may be more effective than providing incentives on capital costs, whereas in other areas, where private driveways or garages are more common, capital incentives rather than investment in charging infrastructures may be more effective.

Concerning EV-grid interactions, impact analyses often use boundary condition penetration scenarios, e.g. by computing upper estimates of the number of electric vehicles that could be supported by specific grid system configurations. In this context, given the current state of the grid and the potential spatial heterogeneity of electric vehicle uptake, reliable spatially disaggregated projections of market penetrations would be useful to identify the areas where grid overload problems are likely to occur first.

The natural domain for modelling EV adoption and for forecasting penetration is the car purchase/ownership modelling framework. Before beginning a review of specific models involving electric vehicles, however, we will give brief overview of the general car ownership modelling context. After reviewing electric vehicle adoption modelling per se, this section will discuss how vehicle ownership and use have traditionally been modelled jointly in the transport literature.

2.3.1 Adoption modelling

Traditionally, the development of prediction models for car ownership and use serve a variety of purposes that encompass the interests of several entities. Examples of these entities are listed by Train (1986) and de Jong et al. (2004), but can be summarised as follow:

- Car manufacturers use models to assess consumer valuation of car attributes;
- Energy companies, oil companies specifically, want to forecast the use of their product, therefore are interested in forecasting both car ownership and use;
- Financial institutions and international organisations use these models for investment decision making assistance;
- Governments make use of car ownership models to forecast impacts of changes in taxation levels, but also to forecast tax revenues;
- Government institutions from national to local level use car ownership and use models to forecast transport demand (in which case these models are integrated with traditional four-step models for transport demand), energy demand and emission levels, and to simulate policy impacts on the demand.
- Utilities have used automobile demand models to forecast potential demand of electric vehicles to estimate the potential additional demand for electricity.

Car ownership models can be classified into the two broad categories of aggregate and disaggregate models. The first category is typically used when data is scarce or where it is difficult and expensive to collect individual data on car ownership. Aggregate models typically predict the fleet size in a given area as a function of average car price, average household income or GDP (aggregate time series models) and demographic characteristics of the population (cohort-based models). Aggregate models can only predict fleet size, while to address most problems in the above list, more detailed fleet characterisations must be forecasted. Disaggregate models can add several details in the description of a forecasted fleet: principally its composition in terms of vehicle types. Typical classes of disaggregate car ownership models are:

- Discrete choice models of number of cars owned by a household (Bates et al., 1978a, Bates et al., 1978b);
- Joint discrete-continuous models for car ownership and use, in which vehicle ownership is modelled as a discrete choice and annual driving distance is modelled as a continuous variable (Train, 1986, de Jong, Hensher, 1992, Golob et al., 1997a, Bhat and Sen, 2006, Bhat and Misra, 1999, Ahn et al., 2008);
- Disaggregate discrete choice models for vehicle type choice. de Jong et al. (2004) in their review of car ownership models define as “very influential” the works on

vehicle type choice modelling by Manski and Sherman (1980), Train (1986) and Hensher (1992), for their treatment of detailed vehicle types.

The use of vehicle type choice models has indeed allowed the development of demand models for electric vehicles and alternative fuel vehicles. Discrete choice models for car ownership and car type are static models; therefore they are best suited for long term prediction. For shorter term prediction, dynamic models are necessary so that changes in household vehicle holdings can be modelled. This is achieved with dynamic transaction models. Model systems in this case include transaction type choice models, in which a household may decide to purchase a car, replace a car or do nothing, see for example, (Brownstone et al., 1996).

The study of EV demand introduces specific challenges to car ownership modelling. A major critical point is caused by the necessity to rely mostly on stated response (SR) data for model estimation, since market data is scarce and still comes from the specific segment of EV enthusiasts. Although stated response surveys have been widely used to forecast consumer response to new technologies, the use of these techniques for EV demand study is particularly difficult because SR tasks involving EV require large deviations from common experience of car usage and common understanding of vehicle attributes in relation to mobility needs. Further challenges are the incorporation in the models of the effects of environmental and other attitudes in shaping adoption and use behaviour.

The three subsections below review electric vehicle choice modelling and the data connected challenges. The review first addresses traditional discrete choice models, then more recent developments extending the traditional random utility framework, and finally the necessity to rely on stated preference data and the limitation this poses.

DISCRETE CHOICE MODELS

Most of the electric vehicle adoption models we find in the literature are Random Utility Discrete Choice Models (DCM) because they allow modelling of the demand for vehicles, by vehicle type. In DCM theory, the individual chooses between a complete set of exclusive alternatives (e.g. the vehicle type to own or the number of vehicles to own), from each of which the individual consumer or the household would derive some utility, if the alternative is chosen. According to classical microeconomic theory, the individual will choose the alternative that maximizes his utility. The utility of each alternative depends on the characteristics of the alternatives and the values that each individual places on these characteristics. Because the analyst cannot observe the utility directly, he cannot specify a model providing the choice outcome with invariable success. Thus the concept of Random

Utility becomes necessary (Ben-Akiva and Lerman, 1985a). This means that the utilities are actually random variables; therefore the analyst can only identify the choice probability for each alternative, but not the choice outcome.

The general structure for the utility an individual n places into the alternative i belonging to the choice set J_n can be written as:

$$U_{ni} = V_{ni} + \varepsilon_{ni} \quad \forall i \in J_n \tag{1.1}$$

where V_{ni} is the observable (or systematic) component of the utility, that the analyst can describe as a function of the alternative's attributes and the decision maker's characteristics, while ε_{ni} is the random error component. The distinct sources of randomness that are typically found are: unobserved attributes, unobserved taste variations, measurement errors and imperfect information, instrumental variables, i.e. variables that are related to actual attributes that are though unobserved (Manski, 1973).

The choice probability for alternative i is thus:

$$P(i|J_n) = Pr\left[V_{ni} + \varepsilon_{ni} \geq V_{nj} + \varepsilon_{nj}, \qquad \forall j \in J_n\right] \tag{1.2}$$

Specific discrete choice models are derived under different assumptions of the joint distribution of the error terms of all alternatives within the choice set.

Once choice probabilities for individuals are known, then several aggregation techniques are available to estimate aggregate demand (Ben-Akiva and Lerman, 1985a, Train, 2009).

Daziano and Chiew (2012), compiling from several earlier studies, identify as the most relevant attributes: purchase price, operating costs, driving range, recharging times, refuelling network density (this is clearly specific to liquid fuel vehicles), power, emissions, incentives for adoption and observable consumer characteristics (e.g. gender and education level). The development of discrete choice models for alternative vehicles has seen studies that have pursued an improvement in the explanatory power of the systematic utility by trying to reduce measurement errors of attributes and the characteristics of the unobserved utility.

In particular, work on the characterisation of the error structure has been mainly directed to

- Modelling more flexible substitution patterns amongst alternatives
- Modelling unobserved heterogeneity;

More recent advances in vehicle adoption models have attempted to extend the traditional random utility discrete choice modelling framework in order to account for behavioural aspects that have been demonstrated as important in car purchase decisions, such as symbolic values and attitudes (e.g. status symbol, environmental attitudes and innovativeness) and multidimensional non-directly measurable vehicle attributes (e.g. comfort, safety and new technology reliability). The reader is referred to the following subsection which provides an overview of works adopting modelling techniques enabling this in the low carbon vehicle choice domain.

The earliest studies on electric vehicle demand made use of the Multinomial Logit Models (MNL) (Train, 1980, Calfee, 1985). The MNL is a DCM in which the error terms are assumed to be type I extreme value (or Gumbel) independently and identically distributed (IID). This distributional assumption allows a closed form expression to be contained for the choice probabilities:

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_{j \in J_n} e^{V_{nj}}} \qquad (2.1)$$

The MNL has been widely used in travel demand modelling literature to modelling several types of travel choices especially before the surge in computational power due to the closed form of the choice probabilities that do not require numerical integration (or simulation). This model is also used in empirical applications in this thesis, specifically in Chapter 5. Further discussion about this model, is therefore presented in subsection 5.2.3, where equation (2.1) is also reported[7], for ease of reference.

Calfee (1985) for example, using a 30 tasks stated preference (SP) survey, estimated vehicle parameters at individual levels. He observed great variability in the valuation of vehicle attributes, but a generally high valuation for range. SP survey effects and the way the survey was designed lead to a surprisingly high preference for the EV alternative.

[7] See equation (5.4)

Beggs et al. (1981), instead of using a classical DCM, opt for a model for ranking the Ordered Logit (OL). The OL, instead of providing the choice probability for an alternative, gives the probability for a ranking of the alternatives. Beggs et al. (1981) estimated an OL based on rank data for several vehicle types (either electric having a battery requiring 6-7 hours to recharge or gasoline powered) characterised by different levels in nine vehicle attributes. By ranking 16 different vehicles, they were also able to estimate parameters at an individual level. Their general finding was of a high disutility for limited range and also a general disutility for long refuelling (recharging) time.

Brownstone et al. (1996) collected SP data and specified a model for vehicle transaction and vehicle type choice. The survey was administered in 1993 over a geographically stratified sample of 7383 Californian households, with a yield rate of 66%. In the SP survey respondents were asked to choose between six vehicle types defined by combining three fuel types and two car body types for each fuel type. The fuel types presented in the survey were gasoline, methanol, compressed natural gas and electricity, while the body types considered were car, van and truck. Having made a choice of one of the six alternative vehicles, respondents were asked whether they would replace or add the chosen vehicle to their holding and, in case of replacement, which of their vehicles they would replace (first, second or third). The authors used an MNL to explain the discrete choices among alternatives defined by the combination of vehicle and transaction. Additional alternatives were the disposals (without purchase) of each one of the vehicles in the respondents' household holding. From the estimated parameters, they observed that the refuelling time coefficient was not significant, while the range coefficient was positive and significant. The coefficient of the square of the range was negative (possibly indicating a saturation in the utility for range), although not significant. They also found that the taste parameter for emission level was negative and significant; in particular families with children were more sensitive to emission levels.

Other more recent examples of the use of MNL in modelling electric vehicle choices are the works by Ewing and Sarigöllü (1998), Ewing and Sarigöllü (2000) and Daziano (2013).

Despite the widespread use of the MNL for vehicle choice, mainly thanks to the close form of its choice probabilities, there is a general problem in the forecasted EV market shares. This lies in the constraints in the substitution patterns imposed by MNL's "independence from irrelevant alternatives" property (IIA). IIA implies that, for any two alternatives, the ratio of the probabilities is not dependent on the presence of other alternatives in the choice set, or on their attributes. As a result, MNL models predict that the introduction of a new alternative, the elimination of an existing one, or changes in the attributes of one of the alternative lead to a change in the probability of the other alternatives such that the ratios of probabilities remain the same. This has a serious implication in the distribution patterns. An example of the effect of using an MNL for forecasting the uptake of electric vehicles is provided by Brownstone and Train (1998). Suppose that a small size EV becomes available in the choice of individuals from a population whose choice set was originally characterised by conventional vehicles only. The IIA property fixes the ratio between, say the share of small gasoline cars and large gasoline cars, therefore the share of the newly introduced small EV must draw proportionally from both the share of small and large gasoline cars, so that the ratio above remains constant. Intuition, however, would suggest that the unobserved utilities of small gasoline cars and the small EV would be more correlated than the utility of the EV and large gasoline cars: this would realistically lead to a higher substitution rate between the small EV and small gasoline cars than between the small EV and large gasoline cars. IIA makes the MNL unfit to represent this phenomenon. More flexible substitution patterns can be achieved by the use of specifications other than MNL that relax the IIA property. The Generalised Extreme Value (GEV) framework, (of which the MNL is a special case) provides the means to model various substitution patterns. After MNL the most common GEV model, especially in transport research, is the Nested Logit (NL) model. Transport applications of the NL are found, for example, in Ben-Akiva and Lerman (1985a), while Potoglou and Kanaroglou (2007) and Caulfield et al. (2010) have used NL models to characterise consumers preference for alternative fuel vehicles, although without explicitly considering electric vehicles. Potoglou and Kanaroglou used the nesting structure to account for a higher correlation in the unobserved utility among vehicles within the same class. In the second work the nesting structure accounts for a higher correlation between the unobserved utility of the HEV and AFV alternatives, in respect to the unobserved utility of conventional vehicles. Hess et al. (2011), meanwhile, used a cross nested logit model[8] (CNL) for alternative fuel vehicle choice, including battery electric vehicles and plug-in hybrid electric vehicles. In fact, Hess et al. hypothesised a heightened substitution rate between cars either having the same body class or using the same type of fuel. To account for this in the correlation structure of the unobserved utility, they proposed a CNL model, arguing that a simple NL model would not correctly capture the full correlation pattern across both body type and fuel type dimensions. They found that the CNL model performs better in terms of fit and allows more realistic substitution patterns in forecasting compared to the NL model.

[8] Various versions of the CNL have been proposed by Vovsha (1997), Vovsha and Bekhor (1998), Ben-Akiva and Bierlaire (1999), Papola (2004), Bierlaire (2006) and Wen and Koppelman (2001).

A model that has been widely applied to electric/alternative fuel vehicles demand modelling on account of its flexibility, both in representing substitution patterns and also in representing random variability in the taste parameters for vehicle attributes, is the Mixed Logit model. Here, the error term is specified as the sum of a zero mean type I extreme value term IID and another term with a zero mean whose distribution over individuals and over the alternatives depends in general on observed data, and the underlying parameters of the distribution. Depending on how this second error term is specified (and interpreted), the Mixed Logit model allows the representation of "random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time"[9] (Train, 2009). Because the mixed logit model is also adopted in empirical estimations of the modelling framework developed in this thesis, the mathematical details of its structure are presented in Chapter 5 before it is also applied in model estimation.

Brownstone and Train (1998) used SP data from a 1993 Californian survey[10] to estimate Mixed Logit (and Probit) models with flexible substitution patterns and, for comparison, an MNL specification. They highlighted a diminishing covariance in the unobserved utility for the following pairs of vehicle types: gasoline with methanol, gasoline or methanol with CNG, gasoline or methanol with electric, CNG with electric. They also highlighted a diminishing covariance of the error component for mid-sized or large cars paired with diminishing car sizes. This means that the model predicts a (disproportionately) greater switching from large gasoline cars if a large methanol car is introduced than from small electric vehicles, whereas an MNL would predict a proportionate switching.

Brownstone et al. (2000b) estimated a Mixed Logit model from the merger of the same data as Brownstone and Train (1998) with revealed data of automobile preferences collected in the same survey. In their specification, they allowed random parameters for the fuel type dummy variables, highlighting the presence of a significant taste heterogeneity, which they show to affect the market forecasts.

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[9] McFadden and Train (2000) show, in fact, that the mixed logit model can approximate any choice model.

[10] Data from this survey was previously used to calibrate the MNL-based transactions choice model of Brownstone et al. (1996),

Taste heterogeneity for three vehicle power-train types (internal combustion engine, hybrid electric, electric) was also modelled by Train and Hudson (2000), who additionally specified the parameters of the vehicle attributes as being independently normally distributed (such as operating cost, performance level, EV range, car size). They estimated two sets of parameters based on SP from two sets of individuals exposed to different levels of information about the relationship between power-train technologies and air pollution issues. In general they highlighted a significant positive valuation for EV range and they found a negative valuation for EV "for reasons beyond price, performance and operating costs". The negative valuation for EV was mitigated for the group with a higher level of information. In both groups, the taste heterogeneity for EV range was not very significant but the standard deviation for the coefficient of the dummy variable indicating the EV was both highly significant and fairly large. The hybrid electric vehicle, meanwhile, has a slightly positive valuation, but a very large standard deviation for both groups.

Dagswik et al. (2002), based on stated preference data from Norwegian residents, estimated extensions to the order logit model. Survey respondents were presented with 15 tasks in which they have to rank three hypothetical vehicles, characterised by a number of attributes. The power-train type is among the attributes presented with electric, liquid propane, gasoline and hybrid each being considered. The authors used rank data to estimate several models, with the first being an OL and the others being extensions that allow serial dependence of the utility across the choice tasks, memory or taste persistence effects and unobserved heterogeneity in taste for the different power-train technologies. The models capturing serially correlated utilities and unobserved taste heterogeneity were estimated only on the first choice. For these models, the second and third choices were used to assess the prediction performance, which in general is shown to perform better than the base OL. The base model is also outperformed in goodness of fit. The empirical results show that there is no negative bias against alternative fuel vehicles. Provided that fuel consumption, range and price are the same, therefore, such vehicles could potentially be competitive with conventional gasoline vehicles. Price and range are important attributes, however; with the latter, in particular, according to the authors, preventing EV technology from becoming fully competitive.

Further more recent applications of Mixed Logit models in alternative fuel vehicle choice are those of Hess et al. (2006) and Daziano (2013). Moreover, more recent fully flexible substitution patterns in modelling low emission vehicle choices have been obtained by Daziano and Achtnicht (2013) by making use of the Multinomial probit model. In this model, flexible substitution patterns are not obtained by making use of additional error terms to the zero-mean extreme value type I terms of each alternative specified in order to generate correlation patterns amongst them. Instead, this is done by specifying the full error terms as multivariate normally distributed, with a covariance matrix specified to reflect the hypothesised correlation structure.

HYBRID CHOICE MODELS

Whereas the vehicle ownership models described above are purely based on economic preference, there is a wide range of evidence that alternative fuel vehicle adoption decisions are also determined by symbolic values and attitudes such as social status concerns, environmental attitudes, innovativeness and other meanings that individuals choosing a certain vehicle communicates to themselves and others (Heffner et al., 2006, Heffner et al., 2007, Skippon and Garwood, 2011). These are latent quantities, i.e. unobserved, and, in fact, unobservable by the analyst. In addition, there are also car attributes that, due to their multidimensionality, are almost impossible to quantify. Safety and comfort are two such examples, with each depending on several characteristics of the vehicles and the context in which it is used, but there is not an unambiguous way to measure them.

Attitudes and symbolic variables, therefore, are unobservable factors which nonetheless manifest themselves in the choices people make. Psychometric indicators are one way of revealing these underlying latent attitudes or values, but their direct use as explanatory variables in the systematic utility of an alternative in a choice model is not advisable for several reasons. These include the following (Daly et al., 2012):

- Attitudinal statements may not translate into a causal relationship with choice;
- Future indicator values cannot be predicted for future populations, thus cannot be used as exploratory variable in forecasting choices;
- They may be characterised by measurement errors, leading to inconsistent estimates;
- It is quite likely that unobserved effects influence an individual's choice and his/her responses to psychometric indicator questions. This leads to correlation between the error term and the indicator, causing endogeneity bias.

Similarly, using a proxy as explanatory an variable for complex multidimensional attributes such safety would lead to biased parameter estimates (Daziano and Chiew, 2012). In order to make use of this type of information to inform choice models, therefore, novel approaches extending traditional DCM have been developed.

The term Hybrid Choice Models (HCM) generally refers to this class of models extending random utility DCM to enable the type of information described above to be accounted for (Ben-Akiva et al., 1999b, Walker, 2001, Walker and Ben-Akiva, 2002, Ben-Akiva et al., 2002). Examples of applications of this class of models in electric vehicle or alternative fuel vehicle choices are the use of a latent class model by Hidrue et al. (2011) to identify a latent class of potential vehicle adopters more inclined towards electric vehicles, together with Daziano and Bolduc (2011) and Glerum et al. (2013b) who each use HCMs to account for environmental preferences in vehicle adoption behaviour. Also Jensen et al. (2013) specify a hybrid choice model to evaluate the impact of attitudes towards environment in the choice of electric vehicles, but using a two wave stated preference survey, before and after practical experience with driving EVs, they show that the positive effects of such impacts on EV preference is stable. Daziano (2012) use HCM to model the effect of safety in vehicle choice.

A general framework for vehicle choices to include all these aspects, and others, typically treated separately, is presented by Daziano and Chiew (2012) who analysed in a systematic manner the data requirements for these types, specifically considering the field of electric vehicle demand estimation. Besides vehicle attributes, these models require measures of latent variables indicators which they classify as perceptual, behavioural and [proper] vehicle attributes. The first are self-reported opinions and subjective evaluations, the second are self-reported or observed behaviour and the third are observable or instrumental vehicle attributes. Such indicators, together with the choice outcome, are manifestations of the underlying latent variables that are modelled as a function of causal indicators (socio-demographics, knowledge about alternative fuel vehicles including environmental benefits, measureable vehicle features, existence of safety equipment etc...). Thus, data regarding causal indicators also needs to be available for the estimation of such models. This demonstrates how behaviourally rich modelling formulations have a drawback of heavy data requirements. It remains unclear whether the heavier data requirements and model complexity are paid off by the real benefits in practical applications of these models in real-world problems. Indeed, leading experts in the field, discussing the use of integrated latent variable choice models, amongst the most widely used HCMs, appear agreeing that "existing studies have filed to demonstrate conclusively the value of these models to practitioners and policy makers" (Daly and Hess, 2013).

RELIANCE ON STATED PREFERENCE DATA

Demand models for new technologies cannot be estimated using actual market data, since such data is, inherently scarce or non-existing. All the models presented in the previous paragraph were estimated using stated preference data (alone or pooled with revealed preference data). It is well known that SP data is susceptible to biases that can be partially mitigated by appropriate survey design. Examples of these biases are (Train and Hudson, 2000):

- Please the interviewer effects (respondents may choose what they think the interviewer wants);
- Halo effects (respondents may choose what makes them feel good about themselves even though their actual choice may be different in real situations);
- Paper money effects (respondents may undervalue the costs of an alternative as they are not buying it for real);
- Salience effects (respondents may evaluate the alternatives only based on the attributes with which they are presented in the choice task whereas, in real situations they would also consider other characteristics);
- Fatigue effects (respondents may become disengaged in long surveys with many choice tasks and adopt random or a systematic answer technique).

These are not the only limitations of SP data, however. Further issues arise when the hypothetical situation involves a new technology viewed by the proponents as a potential substitute for some well-established technology, which implies some changes in the way it satisfies a set of needs currently satisfied by the established technology. Stated more clearly, issues arise in using SP for the evaluation of a new product when the use of such a product entails consumer adaptation with respect to the habitual use of the established competing product. Below we discuss how the negative valuation for limited range invariably found in the results from the demand models in the previous paragraph, may have been exacerbated by SPs failure to take into account consumers' adaptability.

A series of studies carried out by researchers at the University of California, Davis, has supplied evidence of the adaptability of multi-car households to limited range (Turrentine et al., 1992, Kurani et al., 1996). Turrentine et al. (1992) used purchase intention and range simulation games (PIREG), to study the adaptability of households to limited range. PIREG is a gaming and simulation technique developed *ad hoc* to study households' response to range recharging constraints. Households participating to PIREG were asked to record a week long activity-travel diary. After this stage, the drivers in the households were asked to adjust their activity-travel patterns so as to achieve consistency with an EV operating limitation in the hypothetical situation. After analysing the possible strategies to deal with EV's charging requirements and limited range, drivers were questioned about their likelihood of purchasing an EV. The authors found that participants propose simple solutions to cope with these constraints: vehicle swapping, opportunity charging at work or even increasing their vehicle stock. They also highlight that among the public there is a general lack of awareness of range needs. Many PIREG participants were actually surprised by the ease with which EV characteristics fitted their travel needs and showed receptiveness to EVs if prices were comparable to those of gasoline cars.

The authors criticise the results from previous studies based on stated preference because they cannot capture the effect of adaptability of households to limited range. They argue that the high penalty for limited range observed in SP surveys can be explained by the fact that consumer responses are grounded on past experience with conventional vehicles, while PIREG simulations demonstrate that such a penalty is reduced as respondents acquire more information and realise they can adapt to EV's operating limitations.

A drawback affecting gaming and simulation (GS) methods such as PIREG is surveying tool complexity. This is almost unavoidable if complex behaviour has to be elicited. In turn, this complexity presents the disadvantage of making it difficult to achieve the large sample sizes needed for model estimation (Faivre D'Arcier et al., 1998). Reflexive surveys represent an attempt to adapt the principles of GS techniques to large samples. Kurani et al. (1996) developed a multistage mail-based reflexive survey to analyse EV purchase decisions. In this survey the vehicle choice tasks are presented to the respondents after a series of other stages. These comprise: keeping a travel diary for a week and building a visualisation of it as a timeline; plotting their activity locations on a map answering reflexive questions on the timeline, the map and travel related problems based on their revealed diaries. A high level of task complexity, and therefore richness in information was gathered, and this was maintained despite the large sample reached (740 households with a 61% response rate). A disadvantage of this approach lays in the respondent burden of undertaking a multistage (multiday) task.

The critique by Turrentine et al. (1992), reiterated by Kurani et al. (1996), regarding the use of stated preference data for studying the demand for electric vehicles is valid in that SP tasks themselves cannot provide experience of the new product. In SP tasks, EVs can only be described in terms of attributes, some of which will be unfamiliar to the respondents or interpreted through their experience of conventional vehicles. The choice outcome in the SP survey is, therefore, certainly influenced by this unbalanced experience. This critique of the use of SP for EV demand should not be addressed at the SP method itself, however, but rather on how it is applied and for which purpose. In the estimation of the models we presented in the first part of the present section, the SP outcomes actually reflect the interpretation of the EV attributes in respondents' current perception. If the objective is to forecast demand within such a context, therefore, then these models appear appropriate, unless it can be demonstrated that the valuation of vehicle attributes is unstable and volatile, as appears to be the case for limited range from PIREG and other qualitative analyses (Kurani et al., 1994).

If, however, the objective is to analyse the development of the EV market in a context of higher consumer awareness of how their travel needs can be satisfied by EV technology, then the traditional SP approach is likely to fail, since consumers do not achieve such awareness simply by comparing the attribute levels of the proposed alternatives. A reflexive process prior to the SP choice tasks, similar to that proposed by Kurani et al. (1996), could instead enhance consumer awareness and mitigate the effect of experience unbalance in the valuation of vehicle attributes.

More recently SP surveys have been used in combination with electric vehicle trials to actually asses the stability of preferences before and after users' practical experience with electric vehicles. A very recent example of such approach was developed by Jensen et al. (2014), who designed a panel survey to measure the formation of preference for EV and charging infrastructure. Analysing before and after use stated choice experiment data they find that after experience the users choose electric vehicles half as often as before experience. Analysing collected attitudinal data they found that although experience generally brought a more positive view of EV driving performances, they found that experience would increase rather than reduce the concern towards being able to maintain their mobility level. Moreover Jensen et al. (2013) analysing data form a pilot of the study discussed above they found in particular that concern over the driving range increases after experience. This shows that even if drivers can adapt to limited range, this does not necessarily result in a lower utility for range. On the contrary, experience may induce more awareness for vehicle with lower mobility constraints.

Another approach has been proposed to gather data for forecasting new or pre market products. In the marketing field for example a methodology called Information acceleration approach has been proposed (Urban et al., 1997). This approach is based on providing consumers virtual multimedia stimuli. Information acceleration was used by Urban et al. (1994) to generate a virtual environment in which a potential consumer could enter in a virtual showroom, "could 'walk' around the car, 'climb in,' and discuss the car with a salesperson" (Urban et al., 1997). In addition also test drives were enabled. This approach the advantage of being able to simulate complex environments, the presentation of the products is more vivid than in traditional surveys. However, though possibly less costly than electric vehicle trials combined with SP this methodology, still appears complex and costly to develop.

2.3.2 Models of EV use as annual distance driven

The studies reviewed above focus on vehicle adoption modelling and forecasting. Most of the questions that need to be answered in impact assessments of electric vehicle deployment, however, e.g. around energy consumption, air quality, additional load on power grid systems, also require the use of modelling.

Train (1986) developed an integrated model system for automobile ownership and use. It consists of separate sub-models for the choice of number of cars owned by a household, for class and vintage of each cars and the annual mileage travelled by each of them. The demand function for the annual mileage driven is obtained from the conditional indirect utility function, using Roy's identity, given that the choice is of a specific vehicle.

The already mentioned vehicle type and transaction type choice model developed by Brownstone et al. (1996) is actually a building block of an integrated demand modelling system for clean vehicles, capable of forecasting demand for new and used vehicles, annual vehicle mileage and electric charging demand (Brownstone et al., 1994). The vehicle use sub-model is based on structural equation modelling (Golob et al., 1997a). The endogenous variables are vehicle annual mileage and driver's age, gender and employment status. Vehicle and household characteristics are exogenous. In this case, vehicle use is modelled separately from vehicle ownership

Bhat and Sen (2006) developed a multiple discrete-continuous model for the probability for composition and size of households' vehicle holding jointly with the annual distance driven by vehicle. Ahn et al. (2008), meanwhile, used this model for forecasting the adoption and use alternative fuel vehicles, although without considering electric vehicles among the alternatives.

Glerum et al. (2013a) propose a dynamic discrete-continuous choice model, embedding a discrete continuous model into a dynamic programming framework. This methodology allows vehicle transaction type over time, fuel type of the vehicle, ownership status over time and annual vehicle use to be modelling jointly. Because vehicle fuel type choice is modelled, the model has potential applications in analysing the demand for alternative fuel vehicles, including EVs.

The frameworks of Train, Brownstone et al., Bhat and Sen and Glerum et al. can be used for forecasting annual energy demand from EV use. These modelling systems, however, have a drawback in that they can rely on revealed usage data only for existing vehicles. In the estimation of the annual mileage, therefore, the potential effects of the limited range of battery electric vehicles is not accounted for. Moreover, while the mileage metric can provide information on annual energy use, it does not give information on the space and time patterns of charging demand, which is needed to generate load profiles by time of day if we are to analyse the impact of electric vehicles on power grids and to accurately estimate emissions, given the scale of the time-dependence of the marginal emission factor of the electricity generation mix of a grid system.

2.4 Short period models (SPMs)

Often EV use and charging demand need to be modelled at a very fine grained time resolution of the order of the hour or fraction of the hour. This type of short period modelling is of use for purposes such as the following.

- Verifying that electricity generation capacity can provide for the additional load caused by EV;
- Evaluating the costs of the electricity generation for electric vehicle charging, (as marginal costs are time dependent);
- Assessing whether EV associated load will generate congestion at bottlenecks in the distribution network;
- Appraising the effectiveness of demand side management strategies such as direct control of the charging operation by utilities or pricing policies in optimising the load from EV charging, so that
    - grid power system operations can be enhanced,
    - costly investment for grid upgrades can be minimised,
    - Ensuring supply reliability when an increased share of wind power (or other variable renewable energy sources) is added to a grid system.
- In the case of plug-in hybrid electric vehicles (PHEV), estimating with more precision than with models based on annual usage the extent of liquid fuel displacement in favour of electricity, by taking into account the actual recharging opportunities during the course of the day;
- Obtaining more precise estimates of greenhouse gases (GHGs) and pollutant emissions, taking into account the time dependence of the (marginal) emission factor.

As mentioned earlier, SPMs fall into the aggregate or disaggregate category depending on whether travel and charging demand are modelled at the level of the individual or vehicle level or aggregated over a regional fleet. Needless to say, in most cases, the outputs of the analyses require a certain level of aggregation; therefore, even the outputs of vehicle (or individual) level models are typically aggregated to the necessary level.

Aggregate SPMs generally make use of EV penetration scenarios and the distribution of daily distances. or a representative daily distance over a region. to model daily energy requirements, and as well as of the distribution of arrival times at home to model the start times of the charging operation. If distributions are used for both quantities, a joint distribution for the region is derived. In some cases, the charging start time is postulated between specific intervals to model uncontrolled or off-peak charging. Furthermore, in some cases, the energy requirements can also be postulated, typically to model the upper boundary of the energy demand.

Disaggregate SPMs can be further classified as trip-based, activity-based and Markov Chain models of vehicle state. All of these are disaggregate in that each vehicle or driver is an agent with its own travel patterns and energy requirements. The distinction between disaggregate SPMs amongst the three classes above, however, is based on how the vehicle use patterns are modelled. In trip-based approaches, vehicle use is generated by assigning a number of day trips to vehicles, with distances extracted by trip distance distributions and charging start times extracted from arrival time distributions at the location where the vehicle can be charged according to specific infrastructure scenarios (typically the locations are home or work). In activity based approaches, the vehicle is assigned a consistent schedule (typically one day long, or more): the schedule is actually obtained from vehicle diaries extracted from regional or national travel surveys, collected in ad-hoc surveys or obtained from GPS data. The model developed by Soares et al. (2011) belongs to the third category, in which a one year EV pattern is generated by a discrete time state Markov Chain to define the state of each EV agent in each 30 minute interval over one year. The states in which a vehicle can be are: driving, parked in a residential area, parked in a commercial area and parked in an industrial area. Initial state and transition probabilities are obtained from statistical information regarding traffic patterns in the region of analysis (the Porto area in Portugal for the specific case).

Most SPMs make use of charging scenarios to generate power demand profiles from EV charging. These scenarios are typically based on actual policy variables, such as charging infrastructure availability and characteristics of the charging facilities (installed charging power) and predetermined charging behaviours, or charging strategies, to simulate a boundary conditions demand response to electricity tariff structures. Typical charging behaviour scenarios found in the literature are:

- Uncontrolled charging - also referred to as “uncoordinated charging”. This implies that the charging operation starts as soon as vehicles reach locations with charging opportunities (defined by charging infrastructure scenarios) and is carried out until the vehicle is fully charged or leaves to reach the next destination. While in disaggregate models, and activity based approaches specifically, charging terminates with vehicle departure, even if the battery is not full, aggregate models often assume that vehicles are always charged fully.

- Delayed charging – vehicles are assumed to delay charging for a number of hours, so that charging starts in the evening, to ensure electricity costs are minimised. This scenario is intended to simulate the demand response effect to lower night-time prices of electricity, on assumption that the price difference is high enough to induce the large majority of EV users to charge during low price hours.
- Off-peak charging – vehicles are assumed to charge only in off-peak hours. This scenario requires direct control by the system operator. The underlying behavioural assumption is that users accept this type of direct control. Clearly this type of control could also be implemented in a decentralised way by on-board ICT systems, receiving signals from the system controller, although these could potentially be overruled by the user. With this alternative implementation method the validity of the scenario rests on the extent users allow only off-peak charging. In fact, the off-peak charging scenario may be thought of as simulating the ideal effect of electricity tariffs designed to discourage charging in peak hours.

Apart from the charging behaviour scenarios described above, other types of charging strategies can be implemented in EV-grid models in order to coordinate charging of electric vehicles so that the impacts of EVS on the environment or on the grid are minimised. These types of optimisation strategies, which require either centralised direct control or decentralised control through pricing signals, are collectively denominated as "smart charging" or "coordinated charging".

The need to use these behaviour scenarios is due to the fact that, with a few notable exceptions (Galus and Andersson, 2008, Waraich et al., 2009, Galus and Andersson, 2009, Dong and Lin, 2012, Galus et al., 2012b) these models are not actually policy sensitive, since they lack explicit, price sensitive, consumer models for charging behaviour. It should be noted, however, that the lack of explicit charging behaviour models is mainly due to the lack of available data on charging. Although, as has been mentioned, some results from electric vehicle trials have started to be published, the original datasets are not easily available on account of proprietary or participant privacy issues. This is indeed a barrier for the development and empirical estimation of policy sensitive charging models, i.e. in which the response of drivers is the results of underlying behavioural models calibrated on charging behaviour data. A typical example would be that of models based on consumer theory in which charging strategies are the result of empirically elicited driver preferences.

Table 3 provides a summary of works adopting time of day models of electric vehicle use and charging. For each work the table shows: whether the models used are aggregate or disaggregate; the scope of the analyses (i.e. the range of EV deployment aspects encompassed in each work); the assumptions in terms of charging infrastructure and behaviour adopted; the region which the analyses refer to, and; the relevant findings.

It should be observed at this point that disaggregate models have higher data and computational requirements than aggregate models since they are intended to account for heterogeneity in vehicle usage patterns by modelling each vehicle pattern separately. When outputs are aggregated for analyses at regional levels, part of the variability is partly smoothed, therefore one could argue that in such cases aggregate models may be preferable. Often, however, several scales may be of interest for the same type of assessment, and several assessments requiring different scales of analysis may be of interest, although not necessarily immediately. Unlike disaggregate models, aggregate models do not offer the flexibility to extend the scope of the work of analysis. Moreover, while data availability still remains an issue for electric vehicle analysis, high computational requirements are of relative importance given today's facilities, especially in academic environments.

The next section will review a few prominent disaggregate models with a specific focus on the activity based approach.

Table 3 Summary of studies using short period models of electric vehicle use and charging

REFERENCE	MODEL TYPE (1)	ANALYSIS SCOPES (2)	EV TYPES (3)	CH. INFRAS. AVAILABILITY SCENARIOS	CHARGING BEHAVIOUR SCENARIOS	GEO. AREA	RELEVANT FINDINGS
Axsen and Kurani (2010)	DVIL	EEI&P CIP	PHEV	Wherever socket is available; Wherever socket is available & Work	Uncontrolled; Off-peak	United States	• (+) With consumer-designed PHEV most gasoline reduction is caused by charge sustaining fuel economy, not by gasoline displacement with electricity in charge depleting mode; • (+) Uncontrolled charging where sockets are actually available generates more dispersed charging at early hours; • (-) Increasing non-home charging opportunities may displace more gasoline but, in some areas, induce an increased peak load; • (-) Off-peak charging reduces gasoline displacement by electricity.
Axsen et al. (2011)	DVIL		PHEV	Wherever socket is available; Wherever socket is available & Work	Uncontrolled; Off-peak	United States	• (+) Consumer-designed PHEVs can reduce “source-to-wheel” GHG emissions compared to conventional vehicles; • (+) PHEVs can also reduce GHG emissions relative to AE-20 or AE-40 designs when electricity is generated by sources with emissions above 600 gCO2/kWh.

REFERENCE	MODEL TYPE (1)	ANALYSIS SCOPES (2)						EV TYPES (3)	CH. INFRAS. AVAILABILITY SCENARIOS	CHARGING BEHAVIOUR SCENARIOS	GEO. AREA	RELEVANT FINDINGS
Clement-Nyns et al. (2010)	ARL		DNI&P		SM&DM			PHEV	Not specified	Uncontrolled (uncoordinated);	Belgium (to model domestic load, with no EV)	• (-) Coordinated charging can reduce power losses and voltage deviation by peak-flattening.
Darabi and Ferdowsi (2011)	DVIL						CIP	PHEV	[-]	Uncontrolled; Delayed; Off-peak	United States	• (+/-) The all-electric range has a direct effect on charging profiles.
De Ridder et al. (2013)	DVIL							BEV	[-]	Minimum cost allowing the completion of travel schedule	Flanders	• Proves algorithm that generates EV charging schedules, taking into account maximum power constraints at each charging location and the individual EV energy requirements.
Denholm and Short (2006)	ARL	EGI&P		V2G	SM&DM	EconI		PHEV	[-]	Off-peak charging by direct control; or decentralised intelligent vehicle response to real-time price signals (uncontrolled charging not analysed)	United States (6 region)	• (+) Limited negative impacts on generation requirements if utilities can partially control timing of charging; • (+) Dispatchable load by PHEVs could increase minimum system load, increase the utilization of baseload units, and decrease plant cycling (i.e. reduced cost for O&M); • (+) PHEVs are suited for short-term ancillary services, moderate penetration of PHEVs could replace a substantial fraction of the capacity for “super peak” and peak reserve margin.

REFERENCE	MODEL TYPE (1)	ANALYSIS SCOPES (2)						EV TYPES (3)	CH. INFRAS. AVAILABILITY SCENARIOS	CHARGING BEHAVIOUR SCENARIOS	GEO. AREA	RELEVANT FINDINGS
Dong and Lin (2012)	DVIL				EEI&P		CIP	PHEV		Charging behaviour model based on bounded rationality		• (+) Public charging favours small battery PHEVs since these allow day recharging to make up for battery capacity; • (+) Public charging considerably reduces liquid fuel consumption.
Druitt and Früh (2012)	DVIL	EGI&P	V2G	SM&DM		EconI		BEV	[-]	Charge upon arrival at home between 10pm and 6am & only when necessary to complete next trip after work (return) commute. Note that trip purposes are assigned based on time of travel, for trips not belonging to the classification above, charging takes place after a random delay	United Kingdom	• (+) EV charging can reduce variability in national load profile (if demand management in place); • (+) A high EV adoption level allows greater wind and nuclear generation shares in same generation mix; • (+) V2G in addition to demand management increases the contribution of EV to balancing during peak periods; • (-) Modest profitability for EV owners from balancing services when V2G in place (even reduced if only demand management is in place)

REFERENCE	MODEL TYPE (1)	ANALYSIS SCOPES (2)					EV TYPES (3)	CH. INFRAS. AVAILABILITY SCENARIOS	CHARGING BEHAVIOUR SCENARIOS	GEO. AREA	RELEVANT FINDINGS
Grahn et al. (2013)	DVIL			EEI&P			PHEV	Home	Uncontrolled	Synthetic data	• (+/-) If charging occurs only at home, then it is most likely in the afternoon and PHEVs represent around one third of the total load at peak and a 5th of the daily domestic electricity consumption.
Hodge et al. (2011)	DVIL			EEI&P			PHEV		Uncontrolled; Off-peak; As late as possible for a full charge next day	Alexandria, VA	• (+) Small increases by introduction of PHEV in both total electricity demand and peak power; • (+) Gasoline usage greatly influenced by charging scenarios; • (+/-) CO_2 and NOx emissions would decrease, but SO_2 emissions increase due to the use of coal-based generation.
Huang et al. (2012)	DVIL	DNI&P	SM&DM		EconI	CIP	BEV	Home; public	Charge whenever at home & public charging when SOC below a limit; charging only at home and price is at lowest level, provided that minimum SOC is always kept (if SOC goes below charging can occur either home or at public stations)	Indianapolis	• (-) Vehicle usage varies greatly from zone to zone, thus impacts on the distribution grid may be different (more significant in higher EV penetration zones)

REFERENCE	MODEL TYPE (1)	ANALYSIS SCOPES (2)			EV TYPES (3)	CH. INFRAS. AVAILABILITY SCENARIOS	CHARGING BEHAVIOUR SCENARIOS	GEO. AREA	RELEVANT FINDINGS
Kang and Recker (2009)	DVIL			EEI&P	PHEV	Home; Public/private parking places	Uncontrolled end of day; Uncontrolled; Off-peak	California	• (+) Public parking facilities enable more daytime charging, allowing 60–70% of mileage to displace from fuel to electricity, and 80–90% for PHEV60; • (+/-) Not certain that off-peak charging favours energy efficiency.
Kejun et al. (2011)	ARL	DNI&P	SM&DM		PEV	Home; "Public" (home and work)	Uncontrolled; Off-peak	United Kingdom (to model domestic load, with no EV)	• (-) 20% level of EV penetration would lead to a 35.8% increase in peak load, for the scenario of uncontrolled domestic (i.e. the "worst case" scenario); • (+) smart charging beneficial to distribution network.
Kelly et al. (2012)	DVIL			EEI&P	PHEV	Home only; Home and work	Uncontrolled; Off-peak; Last minute; Minimum dwell time	United States	• (+) A compact vehicle with a 10.4 kWh useable battery capacity has a utility factor between 63% and 78%; • (+/-) As travel patterns vary with demographics so do the charging profiles.

REFERENCE	MODEL TYPE (1)	ANALYSIS SCOPES (2)				EV TYPES (3)	CH. INFRAS. AVAILABILITY SCENARIOS	CHARGING BEHAVIOUR SCENARIOS	GEO. AREA	RELEVANT FINDINGS
Khan and Kockelman (2012) (*)	DVIL			EEI&P	EconI	PEV	[-]	Once a day charging	Seattle	• (+) BEVs feasible for significant share of households in Seattle area (single or multivehicle); • (+) Average single vehicle household saves 500$ with PHEV instead of ICEV
Kintner-Meyer et al. (2007)	ARL	EGI&P	√	EEI&P	EconI	PHEV	Home only; Home and work	Uncontrolled; Delayed	13 North American Electric Reliability Corporation sub-regions	• (+) Total electric energy requirement for the entire electric vehicle fleet modest compared to total production for non-transportation use; • (+/-) Cost impact higher depending on regional capacity (where capacity is tight in current state, higher the costs in PHEV scenarios); • (+/-) Impact of CO_2 emissions is variable on a regional basis, depending on marginal generation (charging strategies have different effects based on marginal generation).

REFERENCE	MODEL TYPE (1)	ANALYSIS SCOPES (2)	EV TYPES (3)	CH. INFRAS. AVAILABILITY SCENARIOS	CHARGING BEHAVIOUR SCENARIOS	GEO. AREA	RELEVANT FINDINGS
Kintner-Meyer et al. (2007)		SM&DM EEI&P	PHEV		[-}	United States (12 regions)	• (+) Current US capacity is enough to power over 70% of the national light duty vehicles fleet driving 33 miles per day on average; • (+/-) GHGs emission would decrease replacing gasoline light duty vehicles with PHEVs, but other pollutant emissions (SO_2 and particulates) may increase due to coal-fired generation plants; • (+) Gasoline use reduction would correspond to over 50% of US imports.
Knapen et al. (2011)	DVIL	SM&DM	PEV	Home & Work	Off-peak; Minimum cost for maximum recharge	Flanders	• Activity-based microsimulation can be used for smart grid design: energy demand and power peaks are obtained as function of charging scenarios.
Knapen et al. (2012)	DVIL		PEV	Home & Work	Uncontrolled; Uncontrolled after last trip; Off-peak; Minimum cost for maximum recharge	Flanders	• (-) Use of PHEVs leads to higher electricity consumption than BEVs; • (+) Current off-peak period is long enough to distribute charging to avoid peaks in demand, while allowing savings for users.

REFERENCE	MODEL TYPE (1)	ANALYSIS SCOPES (2)					EV TYPES (3)	CH. INFRAS. AVAILABILITY SCENARIOS	CHARGING BEHAVIOUR SCENARIOS	GEO. AREA	RELEVANT FINDINGS
Mullan et al. (2011)	ARL	EGI&P		SM&DM		EconI	PEV	[-]	Charging on fixed time interval	Western Australian electricity supply system	• (+) If charging occurs in the night, the supply system is made more efficient by increased baseload utilisation; • (+) Recharging can generate income for electricity suppliers without additional capital investment.
Parks et al. (2007)	ARL	EGI&P		SM&DM	EEI&P	EconI	PHEV	Home only; Everywhere (for the "continuous charging scenario")	Uncontrolled; Delayed; Off-Peak	Xcel Energy Colorado Service Territory	• (-) Increased pressure on peaking generators in uncontrolled charging; • (+) Additional capacity would be required, for large penetrations if minimal charging schedules optimisation in place; • (+/-) Most near-term PHEV charging likely to be derived from gas units: cost of natural gas drives the cost of PHEV charging; mixed impacts in terms of emissions, except for net carbon dioxide reduction.
Soares et al. (2011) and Bessa et al. (2012)	DVIL		DNI&P				BEV	[-]	Charge only when SOC is below a limit; Uncontrolled; Uncontrolled only at the end of the day	Case study based on distribution network of Flores island, Azores	• Impossible to proceed to a 50% replacement without smart grid investments or grid reinforcement investment.

REFERENCE	MODEL TYPE (1)	ANALYSIS SCOPES (2)			EV TYPES (3)	CH. INFRAS. AVAILABILITY SCENARIOS	CHARGING BEHAVIOUR SCENARIOS	GEO. AREA	RELEVANT FINDINGS
Strbac et al. (2010)	DVIL			SM&DM	BEV		Uncontrolled (unconstrained);	Great Britain	• (+) Opportunities to optimise demand to meet distribution constraints; • (+) Savings from network upgrades, can be used to change the control paradigm from passive to active.
Taylor et al. (2009)	ARL		DNI&P	SM&DM	PEV	[-]	Peak; Off-peak	[-]	• (-) Charging behaviours could result in loads beyond what current circuit design can reliably serve.
Wang et al. (2011)	ARL	EGI&P		SM&DM	PHEV	Home	Uncontrolled (unconstrained); Delayed	Illinois electric powers system	• (+) Savings from optimal charging and demand response, when integrating large shares of wind generation.
Waraich et al. (2009); and Waraich et al. (2013)				SM&DM	PHEV		Uncontrolled; Price sensitive charging behaviour model	[-]	• It is demonstrated that the model is policy sensitive to various price based charging demand management policies.

REFERENCE	MODEL TYPE (1)	ANALYSIS SCOPES (2)			EV TYPES (3)	CH. INFRAS. AVAILABILITY SCENARIOS	CHARGING BEHAVIOUR SCENARIOS	GEO. AREA	RELEVANT FINDINGS
Weiller (2011)	DVIL		EEI&P		PHEV	Home; Home & Work; Home, Work & Shopping centres	Uncontrolled; Delayed	United States	• (-) Since driving patterns and power supply systems vary across NERC regions, so too, does the EV charging load (author compares CA to NY); • (+) PHEVs with all-electric range 10-40 miles could cut gasoline consumption by more than 50%; • (+) Marginal carbon dioxide emissions can be reduced by more than 50% @ current average US mix.
Wu et al. (2011)	DVIL	EGI&P	EEI&P		EV	Home; Home, Work & Shopping centres	Uncontrolled	United States	• (-) Uncontrolled charging induces an increase in power system peak load.
Zhang et al. (2011)	DVIL		EEI&P	CIP	PHEV	Home; Home & Work; Anywhere	Uncontrolled; Delayed; Minimum power for full SOC	South Coast Air Basin of California	• (+) Decrease in fuel use by 45%/70% can be achieved with PHEV-16/40 in place of HEV, by home charging only. More relevant to the reduction of cold start pollutants (reductions increase if charging also occurs in other places than home). • (+) Peak demand increases could be mitigated by avoiding uncontrolled charging.

REFERENCE	MODEL TYPE (1)	ANALYSIS SCOPES (2)	EV TYPES (3)	CH. INFRAS. AVAILABILITY SCENARIOS	CHARGING BEHAVIOUR SCENARIOS	GEO. AREA	RELEVANT FINDINGS

(*) In this paper time of day analyses are not carried out, although may be possible.

(1) ARL = Aggregate at regional level; DVIL = Disaggregate at vehicle/individual level.

(2) EGI&P = Electric generation impacts and planning; DNI&P = Distribution network impact and planning; SM&DM = smart charging and demand management; EEI&P = energy and environmental impacts and policy (here by energy impacts are intended mainly in terms of oil-based fuels consumption reductions and environmental impacts in terms of GHG and pollutant emissions into the atmosphere); EconI = economic impacts (mainly to consumers or on the power system); CIP = charging infrastructure planning.

(3) BEV = battery electric vehicles; PHEV = plug-in hybrid electric vehicles; PEV = plug-in electric vehicles (both BEV and PHEV)

2.5 Activity based approach

Disaggregate techniques for time of day EV use and charging pattern modelling generate individual electric vehicle patterns at a time of day timescale. Although some examples of a trip-based approach to EV pattern modelling exist (Druitt and Früh, 2012, Huang et al., 2012), most EV analyses adopt what is broadly called an activity based approach. In activity-based approaches consistent daily activity-travel patterns are analysed, while the trip-based approach requires making assumptions regarding the characteristics of the daily travel pattern structure.[11]

The activity-based analysis framework appears particularly suitable to model electric vehicle daily use and charging patterns because it analyses travel "as daily or multi-day patterns of behaviour, related to and derived from differences in lifestyles and activity participation among the population" (Jones et al., 1990). This type of analysis is particularly appealing as it is rooted in the time of day timescales, obviously absent in vehicle use modelling based on the annual distance driven metric. An activity-based model with a charging behaviour component, allowing users preferences for different charging strategies to be modelled, would allow the effect of charging demand management policies both on charging and travel patterns to be simulated without relying on predefined charging behaviour scenarios.

Before introducing examples of studies where proper activity based models (ABM) have been used for analysing electric vehicle patterns, we review below (in section 2.5.1) analyses that, instead of making use of activity-travel schedules generated by ABM, utilise observed conventional vehicle travel patterns to model electric vehicle use. This is by far the most commonly used approach in impact analyses. Utilisation of observed conventional vehicle diaries is still considered here as part of the activity-based approach, since structurally consistent activity-travel schedules are used for EV pattern modelling.

2.5.1 EV patterns from observed car diaries

Use patterns of conventional (i.e. non-electric) cars have been used as "mock" EV use patterns. This is done in several ways: using travel diaries from existing travel surveys collected by various agencies; collecting car diaries in ad hoc surveys; or using GPS data. The underlying assumption is that the introduction of electric vehicles does not significantly

[11] For example Druitt and Früh (2012) simply assign two daily journeys to each vehicle assigning purposes based on the time of day of the trips (randomly extracted from a time of travel distribution).

change travel patterns, even in large deployment scenarios. This assumption is of course acceptable if the object of the analysis is PHEVs, which do not have range limitations. Concerning battery electric vehicles (BEV), the assumption is justified by the high feasibility of journeys and tours under various charging infrastructures and charging behaviour scenarios. Nevertheless, if time of day road pricing can affect car patterns,[12] the complex tariff structures of electricity for EV charging demand management, and their spatial and temporal variability (e.g. different prices at home, work charging facilities or at other locations), are likely, in principle, to induce price sensitive drivers to adapt their travel patterns to minimise their travel costs.

In the work of Kang and Recker (2009) the PHEV usage patterns are replicas of car diaries extracted from the Travel Diaries of the 2000–2001 California Statewide Household Travel Survey. The charging patterns are generated using infrastructure and charging bahaviour scenarios. It is not clear whether the car diaries generated are vehicle based or person-based, and, in the latter case, whether vehicle use by multiple drivers was accounted for. In fact, neglecting use of one vehicle by multiple drivers would lead to an underestimate of the daily energy needs of the vehicle and to an overestimate of the time the vehicle is available for charging (indeed, neglecting use by multiple drivers is equivalent to assuming that each driver uses a different vehicle). It should be pointed out that, for analyses aiming at assessing the impact of EV charging on the grid at the distribution level, which require not only fine temporal resolution but also fine spatial resolutions, especially in urban contexts, analyses using vehicle-based diaries ensure more accuracy in energy use and time of charging estimates.

In order to assess potential energy impacts in California from "user-designed" PHEVs, Axsen and Kurani (2010) model PHEV use and charging profiles making use of one day car diaries from a previously administered US nation-wide survey designed to assess, *inter alia*, consumer priorities in PHEV designs (Axsen and Kurani, 2009, Axsen et al., 2010) and the effective availability of electric vehicle recharging opportunities in car-owning households (Axsen and Kurani, 2009, Axsen and Kurani, 2012). For the latter task, the travel diary

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[12] TfL (2008) Central London Congestion Charging Scheme Impacts Monitoring; Karlström & Franklin (2009) Behavioral adjustments and equity effects of congestion pricing: Analysis of morning commutes during the Stockholm Trial

collection instrument embedded questions about the availability of electrical outlets and their distance from the car at the parking locations visited during the survey day. One day diaries, charging opportunities data and characteristics of user-designed PHEVs were also used to generate charging profiles that integrated with an energy dispatch model so as to estimate the greenhouse gas emissions. The charging profiles in Axsen and Kurani's work are generated using charging behaviour scenarios and are specified in Table 3, alongside those utilised in other works.

Similar types of analyses are carried out by Kelly et al. (2012). Kelly and colleagues extract one-day vehicle diaries from the US 2009 National Household Travel Survey diaries, and generate aggregate time of week PHEV charging load profiles, making use of charging infrastructure and charging behaviour scenarios.

Khan and Kockelman (2012) use multiday GPS tracked vehicle patterns, to carry out another type of analysis, consisting in the assessment of how electric vehicles (BEVs and PHEVs) can satisfy households' vehicle use needs. From a sample of 255 Seattle households they find that a BEV with a 100 miles range could meet 50% of the needs of single vehicle households and 80% of the needs of multivehicle households, charging once a day and relying on another vehicle or mode just four days in a year. Khan and Kockelman, instead of using current driving data to model EV patterns, assess the potential of EVs to replicate current driving data. Their results show that single vehicle households in Seattle need to change their travel patterns in BEV scenarios, if only one charging opportunity is available. Clearly this may not apply to PHEVs. Incidentally, one of the reasons why many analyses using observed conventional vehicle patterns for EV modelling only involve PHEVs is that the argument for unchanged travel patterns in BEV deployment scenarios is not so convincing, at least in some parts of North America. Nevertheless, even in parts of the world where current driving patterns are more compatible with typical BEV ranges or even in the case of PHEV deployment, the assumption of unchanged travel patterns is arguably challenged by future charging service modes, tariff structures and infrastructure availability, and of course on the driver's preferences in terms of range availability, and cost.

2.5.2 EV patterns from activity based models

The activity based modelling of travel demand, comprising a set of heterogeneous behavioural theories, conceptual frameworks, implementation methods and empirical applications, in essence tries to reconcile travel behaviour modelling and analysis with the common shared perspective that travel behaviour represents just a facet of a complex pattern of behaviours that the analyst observes as the engagement of individuals in activities, and in particular as the result of the fact that this complexity takes place both in space and time. Traditional transport trip-based modelling has lacked a strong foundation in this more holistic philosophy, since in the most often used trip based framework, the Four Step Model (FSM), activities affect mainly trip generation and their influence decreases as the sequence of modelling steps proceed (Mc Nally, 2008). The effort to improve travel demand modelling by adopting ABM frameworks has not been driven purely by the intellectual trend towards solving the dialectics between this philosophy and modelling practice to reach the transcending unity that would appease theoreticians. In fact, the theoretical deficiencies[13] present in the trip-based approach prevent its use in policy analyses beyond “certain well-defined situations” (Mc Nally and Rindt, 2008), which in practice consist of their original objective of urban highway investment analysis (Bates, 2008a). More precisely, the most prominent policy types requiring enquiring tools that would overcome FSM’s limitations were: “global and highly flexible policies”, such as fare changes in public transport and policies that would lead to “substantial [and heterogeneous] travel response”, like road pricing (Bates, 2008a).

Practitioners have indeed introduced improvements to the FSM framework to make it more flexible in reflecting more realistic behavioural responses. These improvements, however, had the aim to obtain more reasonable result at the aggregate level, rather than actually improve behavioural modelling at the individual level. In contrast, at the heart of the development of activity based models there is the representation of the individual decision process as disaggregate.

In order to analyse the effect on travel and electric vehicle charging patterns of policies intended to manage the electric vehicle power demand profile and of travel demand

[13] Mc Nally and Rindt summarise six main theoretical limitations of trip-based models as: “(1) ignorance of travel as a demand derived from activity participation decisions; (2) a focus on individual trips, ignoring the spatial and temporal interrelationship between all trips and activities comprising an individual’s activity pattern; (3) misrepresentation of overall behaviour as an outcome of a true choice process, rather than as defined by a range of complex constraints which delimit (or even define) choice; (4) inadequate specification of the interrelationships between travel and activity participation and scheduling, including activity linkages and interpersonal constraints; (5) misspecification of individual choice sets, resulting from the inability to establish distinct choice alternatives available to the decision maker in a constrained environment; and (6) the construction of models based strictly on the concept of utility maximization, neglecting substantial evidence relative to alternate decision strategies involving household dynamics, information levels, choice complexity, discontinuous specifications, and habit formation”.

management policies on electric vehicle load, ABMs appear particularly suitable for the following reasons;

- Qualitative similarities between road pricing and price based electricity demand response strategies;
- A bottom up structure, which allows flexibility in aggregation, and consequently in analysis goals.

Despite these apparent advantages of ABMs for the type of policy analyses of interest in the realm of electric vehicle deployment, to the author’s knowledge, only a few ABM implementations are documented in the literature. Two prominent examples are the works carried out in Switzerland at ETH (Waraich et al., 2009, Galus et al., 2012b, Waraich et al., 2013) and in Belgium (Knapen et al., 2011, Knapen et al., 2012, De Ridder et al., 2013).

The ETH researchers integrated MATSim, a tool for agent-based activity-based transport modelling (Balmer et al., 2008), with a plug-in electric vehicle and power system simulation tool PMPSS. In MATSim a population of vehicle owners (agents) is generated from census data (or through a population synthesiser if only the marginal distributions of vehicle owner characteristics are available). Based on specific electric vehicle penetration scenarios, each agent is assigned a PEV (a BEV or a PHEV or another vehicle)[14]. Each agent is also assigned a plan of a trip and activities, (the initial demand). In an iteration of MATSim each plan is executed and scored with a utility value (based on the activities in the plan, their durations, delayed arrivals, earlier departures, and early arrivals at locations with opening times) and re-planned, i.e.by adapting time choice; route choice; mode choice; and destination choice. The goal of each agent is to maximize the utility and this is achieved via a co-evolutionary algorithm in which the plans are varied via crossovers and mutations, and by eliminating adaptations with lower utility. In the integrated MATSim-PMPSS, the cost for charging a PEV is also taken into account in the utility. This depends on the price of the electricity at the time when the vehicle is charged and on the amount of energy required (depending on the total time on charge, given a fixed charging power). An additional “charging module is added to the original MATSim configuration, that:

[14] Recently, MATSim and PMPSS have been integrated with an additional vehicle technology simulator allowing the fully integrated model to simulate mixed fleets of BEVs, PHEVs, HEVs and ICEVs (Waraich et al., 2013).

- Assigns charging times to PEVs, based on specific charging scenarios to the cars;
- Assigns the cost of the electricity charged that is used in the evaluation of the plan utility.

The MATSim simulation iterates until a relaxed state has been reached. At this point the charging times, locations and state of charge of the agents are sent to the PMPSS which determines if the load from charging infringes physical network conditions. Depending on the type of analysis being carried out, the PMPSS may feedback a real-time electricity price signal containing network congestion information to the MATSim scheduler, so that the cost of congestion is also included in the scheduling process. In this case, an outer optimisation loop takes place, (see Figure 5).

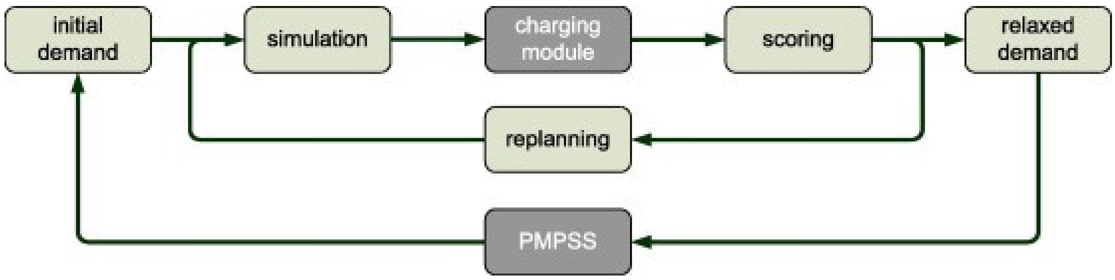

Figure 5 MATSim –PMPSS optimisation loop, reproduced from Waraich et al. (2013). This image has been reproduced with the permission of the rights holder, Elsevier.

Note that the PEV agents are also modelled in the PMPSS system. Here, a game theoretical approach is used to model the charging behaviour of several connected PEVs, both in congested and non-congested networks. The game theoretic approach is applied here to enable modelling competition between PEV agents over potentially scarce energy or network capacity at a certain node of an electric grid. For the details of the PMPSS model we refer specifically to (Galus and Andersson, 2008, Galus and Andersson, 2009, Galus et al., 2012b). Here, we just describe how the utility of PEV agents is defined. PEV agents derive benefit from their individual state of charge (SOC) and they feature an individual value for energy acquisition. At a time interval, while charging, the benefit from charging of an agent is modelled as a quadratic function of the SOC

$$b = \alpha SOC - \beta SOC^2 \; \alpha, \beta > 0 \tag{2.2}$$

The total utility u_T for a PEV agent while charging, at each time interval T of the charging operation, is given by the benefit scaled by a private value θ_T minus the price p_T of electricity times the q_T quantity of energy acquired during the time interval.

$$u_T = \theta_T[\alpha SOC_T + q_T - \beta(SOC_T + q_T)^2] - p_T q_T \tag{2.3}$$

The agent charges as long as the marginal benefit, scaled by θ_T, is above the price of electricity. α and β are scaled so that charging will not take place in case electricity cost is above gasoline cost (accounting for energy conversion efficiencies). Clearly this scaling is perfectly reasonable when PHEVs are involved, given that they can run on both gasoline and electricity, whereas the relevance of this scaling for battery electric vehicle is arguable. The private value decreases as the difference between the desired state of charge at departure and the current state of charge decreases and increases as the current time approaches the departure time. The parameters that define this private value are somewhat arbitrarily defined to obtain curves that increase more or less steeply as the departure times approaches, given the state of charge and desired state of charge. Moreover, the desired state of charge is decided based on the energy required to drive the vehicle to the next location with a charging opportunity, whereas other factors, including range anxiety, seem to be neglected. Thus, the model of charging behaviour although plausible in the case of PHEVs where problems of range limitations do not exist, may be less suitable for describing BEV user behaviour. In any case, this charging behaviour model, while developed to be theoretically coherent with the game-theoretical framework, appears to lack proper empirical backing,[15] both in the calibration of the parameters (apart from the mentioned use of market liquid fuel prices to determine the upper bound of an acceptable electricity price for electric mobility, for the agents) and in the validation of the model structure.

The Belgian work uses the FEATHERS activity based model to generate 24-hour activity-travel schedules from which car schedules are extracted. Vehicle categories, represented by an equivalent internal combustion engine cylinder volume (small, medium and large) are assigned to each car user, reflecting the market share in Flanders. Each equivalent internal combustion engine vehicle category is mapped into a battery capacity and energy consumption category, used to define the characteristics of BEVs or PHEVs. According to pre-set market penetration scenarios, EVs or conventional vehicles are assigned to schedules. Whether the assigned EV is a PHEV or a BEV is determined by market share scenarios and schedule BEV-feasibility. Charging scenarios are used to model charging behaviour, so that the power load from EV charging can be generated. In this work the methodology applied is

[15] Based on revealed or stated preference data

very similar to that described in the previous subsection in which real travel diaries are used to model EV patterns. Here, instead of real travel diaries, ABM generated activity travel schedules are used. The way the ABM is used is not sensitive to electricity pricing because schedules are generated independently from charging behaviour scenarios. In fact, the analysis carried out in this work carries the same weakness of the analyses based on observed travel patterns; it lacks policy sensitivity when it comes to evaluating the potential effects of charging demand strategies on travel patterns.

A similar ABM implementation is also adopted by Hodge et al. (2011), where the energy demand profile in Alexandria, Virginia from PHEV charging under various charging behaviour scenarios, are obtained based on vehicle schedules generated by the TRANSIMS model (Smith et al., 1995).

While this subsection has focus on the use of ABMs in EV pattern analysis, it is worth noting that, despite the much more widespread application in travel demand practice of the FSM approach, compared to ABMs, the literature on EV impact analysis using FSM for EV pattern generation is almost non-existent. The reason for this is that transport academics have almost completely given up publishing on this approach, given the limitations mentioned above for the type of policy analyses that are now required that go far beyond large infrastructure planning. In fact only one example was found by the author of the application of FSM: for the estimation of additional domestic load on the grid by EV deployment (Huang et al., 2012). Huang and colleagues use hourly origin-destination matrices to deduce the number of (electric) vehicles arriving at home in each traffic analysis zone of Indianapolis, together with the total trip length and distance distributions so as to model the quantity of charge required. Amongst the drawbacks of this method, there is the fact that actual trip chaining is neglected. This has possibly negligible effects on aggregate home charging demand (for a given charging behaviour scenario). At the disaggregate level, however, where it is necessary to model nodal congestion on the distribution network, the effect of a lack of behavioural realism may have more profound effects.

2.6 Summary

In this chapter, the techniques that have been used to model the demand for electric vehicle use and charging have been reviewed. Vehicle ownership and annual use models provide forecasts of the market shares of electric vehicles and other vehicle types together with estimates of their annual use, which in turn can be used to obtain annual energy consumption estimates. These models have been widely used by transport modellers for car market research and as tools to anticipate the potential energy security, environmental and power infrastructure impacts of electric vehicle deployment.

For analyses of integrated transport and power systems at much smaller time scales, however, instead of just downscaling annual use to time periods of the order of hours or fractions of hours, other approaches are available which are able to model directly at these timescales. Eventually, the two modelling approaches can be combined into an integrated demand model system resolving the two timescales in a coherent way, taking into account both long-term strategic consumer decisions (e.g. car ownership related decisions) with short term EV use and charging decisions.

Short period modelling approaches have been used mostly to analyse the effects on power systems of the introduction of electric vehicles, but they have also been used for the estimation of the broader energy and environmental impacts of electric vehicle deployment, e.g. the amount of conventional fuel displacement in favour of electricity and GHGs and pollutant emission estimations. Amongst SPMs, the ABMs were identified as the most flexible of these analyses because their disaggregated output can be re-aggregated along the specific dimension of interest to the aggregation level desired. Moreover, disaggregate trip-based models, amongst other advantages, provide more realistic descriptions of travel patterns. Activity based models are also preferred to the other activity based approaches, which make use of observed travel patterns from conventional cars, because the latter cannot overcome the assumption of travel pattern invariance with respect to electric vehicle deployment, whereas ABMs can be implemented to relax this assumption. Another assumption that characterises most models is related to electric vehicle users' charging behaviour. This is not actually explicitly modelled, but is represented using a set of pre-determined charging behaviour scenarios or charging strategies. This approach makes them, *de facto*, policy-insensitive. They are not sensitive for example to electricity tariff structures; therefore they are actually useless to test the effectiveness of pricing policies. In fact, they can only represent the intended effect of a policy and the particular boundary conditions that this may determine, rather than the most likely conditions.

Both the two assumptions mentioned have been partially addressed by the integrated MATSim-PMPSS model system. The first is addressed by also considering the cost of charging in the evaluation of the utility of an agent plan, which in turn depends on the price of electricity for charging at that time of day, and on the energy required to complete the plan. The second assumption, meanwhile, is addressed by defining the charging behaviour model within the PMSS sub-model. As was discussed, however, the charging behaviour model used lacks an empirical foundation. Another example of work in which charging behaviour is modelled explicitly to allow policy sensitive analyses, but which suffers from the same weakness, is the study carried out by Dong and Lin (2012). In fact to the author's knowledge, there are currently no empirically based price sensitive charging behaviour models in existence. Moreover, notwithstanding the importance of the ETH researchers' work in devising a way to integrate aspects of the charging operation into the utility of an activity-travel schedule, analysts' understanding of the extent to which attributes characterising the utility of charging strategies may be traded with attributes defining the utility of an activity-travel schedule still needs expanding. Finally, models including these trade-offs should be developed in forms which will allow their integration into ABM systems.

In section 2.2.1 that reviews electric vehicle adoption modelling 2.2.1, issues related with the reliance on stated preference data have been discussed. One that is particularly important in the context of electric vehicle modelling is the effect that familiarity the technology in determining preferences. In the present studies stated preference data, (stated choice data specifically) are used to analyses electric vehicle use scheduling and charging preferences, amongst drivers without EV experience. In Chapter 4 where the development of the survey tool ECarSim is reported, the approach adopted through which mitigating the lack of familiarity is mitigated is discussed.

The rest of this dissertation introduces a modelling framework for joint travel and charging decisions. Empirical implementations of this framework are carried out in order to advance the understanding of charging behaviour and its interaction with travel choices based on specifically collected data. The potential of these models for relevant policy tests are also assessed. The following chapters thus constitute the original contribution of this research to the modelling and analysis of integrated electro mobility-grid systems.

Chapter 3 CONCEPTUAL AND ANALYTICAL FRAMEWORK

3.1 Overview

This chapter presents the development of a model for electric vehicle (EV) charging behaviour that is embedded within the broader context of activity and travel choices, specifically the time of day (scheduling) aspect. The model adopts a microeconomic perspective within which EV users are assumed to choose amongst alternative EV charging and activity-travel scheduling options, so that their utility is maximised. Hereafter, for ease of presentation, EV charging and activity-travel scheduling options/decisions will be referred to as EV use scheduling and charging (EVUSC) options/decisions.

As shown in Chapter 2, section 2.5.2, when integrating MATSim and PMPSS, Waraich et al. (2013) express, within the utility of an EV activity-travel schedule, the utility from charging purely by its cost. In contrast, here, the utility of an EVUSC alternative depends explicitly on other attributes characterising the EV charging option, beyond the costs. Based on the conceptualisation of the charging choice that will be introduced in section 3.3.1, these other attributes are:

- the available energy after charging (simply referred to using the variable E) which is of course related to the driving range available after charging;

- the (effective) charging duration or charging time (CT), i.e. the time elapsed between the arrival at a location with a charging facility and the time the charging operation terminates (i.e. the sought level of available energy is achieved);
- the charging-induced schedule delay late (CISDL): this variable is used in place of CT when the charging operation is long enough to imply a departure time that is later to the preferred departure time from the charging facility.

Indeed, the conceptual framework developed in the present chapter postulates that charging decisions are contextual to a review of the planned activity-travel schedule. For example an EV user may decide to delay the departure to obtain a higher available energy (or, in other words, a higher battery state of charge, SOC) at departure. In such a situation tradeoffs occur between activity-travel schedule attributes (such as schedule delays) and attributes characterising a charging option (available energy or charging durations), as it will become clear in the rest of this chapter.

This framework, therefore, explicitly captures the effects of available energy (i.e. range) preferences in EV use scheduling and charging. Thus, the possible effects of range anxiety, or rather the propensity to avoid situations leading to range anxiety, which may impact EV charging behaviour and EV travel timing choices can be captured.

In summary, the conceptual and modelling framework presented in this chapter allows both charging choices and travel timing choices to be sensitive to electricity price, but also allows them to be sensitive to the range preferences, which are expected to affect electric vehicle users' charging and travel behaviour when the range resource is limited, as in battery electric vehicles (BEV). In the present chapter, as elsewhere in this thesis, the phrase electric vehicles and the acronym EV refers to BEV, unless otherwise stated.

Before presenting the conceptual and modelling framework used for electric vehicle use and charging behaviour, we review the relevant literature on electric vehicle charging behaviour in order to show how it is generally described. This review also show that while charging behaviour is been currently extensively studied, for example in electric vehicles trials, only few are the attempts to generate predictive empirical models for it that could be applied in demand analysis. Finally analysing the available literature on charging behaviour serves in identify (some) of the formal attributes that characterise the alternative of a charging decision. More specifically, we shall see that the studies of charging behaviour reviewed will justify the adoption of "available energy charged" as attribute of a charging option is charging decisions.

3.2 Relevant literature on charging behaviour

The phrase charging behaviour, or re-charging behaviour, refers to the spatial and temporal patterns of charging events associated with each electric vehicle. Hourly (or half hourly) electricity consumption associated with EV charging is important: to determine the environmental impacts of electric vehicle deployment in terms of greenhouse gas emissions and air quality; and the impacts on the power systems in terms of generation capacity and, more importantly, the capacity at the distribution level of the power grids, etc. For this reason, charging behaviour is represented in terms of so called (re-)charging profiles. A charging profile is a plot of the power demand from the charging of electric vehicles, typically over a 24 hour period. Charging profiles from several vehicles within a geographical region are then aggregated, to provide the total charging demand. If very local impacts need to be analysed (e.g. the onset of congestion at bottlenecks in the distribution network), only local charging events should be aggregated, requiring location specific charging profiles.

Section 2.4 of Chapter 2 discussed how charging behaviour scenarios have been used to generate hourly profiles of power demands from electric vehicle charging as well as providing the spatial features of the demand when coupled with charging infrastructure scenarios. Charging behaviour scenarios have also been termed “theoretical models of charging profiles” (Robison et al. 2013). The archetypal charging behaviour scenarios include: uncontrolled or uncoordinated charging, delayed charging and off-peak charging. Variations on these themes can be found in the literature as was seen in Table 3 of Chapter 2. Data from real world trials in part confirm and in part challenge the assumptions of some of these theoretical scenarios. The following sections present a summary of the observed charging behaviours in real world trials, and in theoretical models of charging behaviour.

3.2.1 Charging behaviour in real world studies

Several electric vehicles trials have been carried out around the world, and a few in the United Kingdom, in which the charging events from participating electric vehicles have been monitored.

In 2009, the charging events of 50 electric vehicles from a BMW Group MINI-E Berlin trial were monitored for a period of one year by researchers at the Ilmenau University of technology (Westermann et al., 2010). Westermann et al. (2010), using a week-long sequence of data for each of the 50 vehicles, observed that not all vehicles were charged every day over that week. It is possible that the non-daily charging frequency observed in the travel week analysed resulted from the fact that some of the vehicles may not have been used every day of the week. However, it may also be possible that not all users prefer “topping-up” their vehicle's battery every day. If this was the case, then it would be at odds with the charging behaviour scenarios that assume charging at every possible opportunity. Indeed in uncontrolled charging scenarios all vehicles are assumed to charge at every opportunity in a given charging infrastructure scenario, when the vehicles' batteries are not already fully charged. To some extent this also applies to delayed and off-peak charging scenarios: where the assumption is that an EV that is not fully charged will charge any time the scenario conditions are met.

The observations by Westermann et al. refer to only one week, without consideration of how representative that week may have been. Nonetheless, similar charging patterns have been confirmed in parallel but independent data collections carried out from the same Berlin MINI-E trial. In particular, Franke and Krems (2013b) collected self-reported weekly charging diaries of 79 MINI-E trial participants and found that the average number of charging events (over the 79 collected diaries) was 3.1. Franke and Krems also reported that this figure was in line with the figure obtained from data acquired from instrumented vehicles throughout the MINI-E Berlin trial (an average of 2.8 charging events per week).

The BMW Group carried out MINI-E trials in other parts of the world leading to similar observations regarding charging frequencies. For example, a large MINI-E trial was carried out in the United States, specifically in the Los Angeles and New York City/New Jersey areas. This involved around 450 vehicles. 24 electric vehicle week-long diaries examined by the University of California, Davis, showed that 13 households charged their MINI-E on a daily basis (at least 6 days during the diary week), whereas lower frequencies of charging events were observed in the rest of the diaries (Turrentine et al., 2011). In the United Kingdom the BMW Group MINI-E trial involved 40 vehicles, 62 individual users and 76 pool users, the average charging events per week were 2.9, as calculated from data logger data (BMWGroup, 2011). During this trial, either special electricity tariffs for night charging or controlled charging was available to the trial participants. The average charging demand was observed to peak after 11pm. The time of occurrence of the peak demand provides evidence that time-of-use pricing can be effective in controlling the position of the demand peak.

Schey et al. (2012) also provide evidence that time-of-use tariffs, when in place, have a distinct effect on electric vehicles charging demand. Charging events were monitored from electric vehicles in Nashville and the San Francisco region in 2011, as part of a nationwide charging infrastructure demonstration, The EV Project, sponsored by the US Department of Energy. Results from the two areas show that, in San Francisco, a spike in the load occurred after midnight on weekdays, whereas in Nashville the demand peaked around 8pm. In San

Francisco, the vast majority of the trial participants' homes, with monitored electric vehicle supply equipment, were located in the service area of the Pacific Gas and Electric Company, which offers a time-of-use rate to EV users. Subscribers to this rate have cheaper electricity at off-peak hours. This very likely explains the spike in demand after midnight. In Nashville, however, no incentive for delaying charging to late night hours is available, explaining the demand peak at 8pm, with a less sharp peak than in San Francisco. Schey et al. do not report information regarding the frequency of charging events.

The CABLED electric vehicle trial took place in Coventry and Birmingham in the West Midlands of the United Kingdom and involved 108 vehicles. The vehicles monitored comprised both private users and fleet vehicles (Everett et al., 2011). This project demonstrated a high sensitivity of electric vehicle users to incentives for charging during off-peak hours. In particular, the participants were offered a £50 incentive for charging during off-peak hours and half of those with smart chargers installed in their homes could pay cheaper electricity when charging off-peak. Everett et al. (2011) report that, in the first three months of the trial, the majority of home recharging events carried out by private participants started between 11pm and 12pm. Fleet vehicles were charged more frequently in daytime hours then privately used vehicles. According to Robinson et al. (2013), in both cities, 18 non-home charging posts at six different city locations were available, where the charging was for free (though, in some cases a parking fee was levied). The prevalence of overnight home charging is likely to reflect the low ratio of public/posts users; however the convenience of charging at home, despite having to pay for charging, may also play a role in charging decisions.

Robinson et al. (2013) analyse the charging patterns from participants of another EV field study in the UK, the Switch EV trial. This project took place in the North East of England and involved 44 vehicles leased for six months to a total of 65 users, both private and organisational. The vehicles leased to organisations were used by individuals or as the organisations' pool vehicles. The organisational users charged more frequently than private users. All drivers made use of home charging starting early in the evening: the peak demand for charging at home was around 6pm. The average number of home recharging events over the trial period was highest for private users, who mostly charged at home. Organisational users mostly charged at work. The average number of recharging events per user was 118.5 over six months (~4.5 events per week). Considering only private users, the average number of recharging events was slightly lower 109.7 (~4.2 per week). These figures are higher than those observed in the Berlin trials though they still suggest that not all EV drivers recharge every day. The time of peak demand for private users charging at home (6pm) is consistent with uncontrolled charging behaviour scenarios or similar, see for example the "end-of-travel-day recharging" and "uncontrolled charging" postulated by Kang and Recker (2009).

A thorough quantitative comparison across these trial results is difficult for the following reasons:

- differences in the time span of the charging data analyses e.g.
  - week-long diaries or data records;
  - several months-long panel data;
- differences in the way the charging demand time of day patterns are reported, e.g.
  - distribution of charging event start times over a period,
  - average number of vehicles on charge at a given time of the day,
  - aggregated time of day power demand profiles.

Nonetheless, some qualitative features regarding charging patterns can be deduced. Overall, the charging patterns from trials seem to show that the basic charging behaviour scenarios, uncontrolled charging and off-peak or delayed charging, can capture the positions of the peaks in demand in the absence and in the presence of time-of-use pricing, respectively. The evidence that the number of charging events per week is low suggests, however, that the charging demand levels expressed by analyses making use of charging behaviour scenarios should be treated with caution. In fact, if the low charging frequency is not purely reflecting the electric vehicle use frequency, but is also the result of charging preferences, then charging behaviour scenarios may overestimate the magnitude of the daily charging demand. Such overestimation would be the result of the fact that, in charging behaviour scenarios, EVs charge whenever the scenario rules allow it, neglecting the effect of idiosyncratic preferences.

It is therefore important to understand how individuals actually decide when to charge their EVs. This motivates the need to explore more in depth the determinants of charging decisions. The works reviewed in the in the next subsection are first attempts in this direction.

3.2.2 Theoretical and empirical models of charging behaviour

The studies mentioned above have merely described charging patterns. They have not attempted to try to identify determinants of charging behaviour for predictive purposes.

The mere description of spatial and temporal patterns tends to underplay the purpose of the charging episode, which is to increase the vehicle's availability for use, in other words acquiring range resource. This applies specifically to BEVs, since, for BEVs, the driving range is a limited resource because it can only be stored in limited quantities through a process that is not instantaneous. In contrast, vehicles that can rely on conventional fuels (such as internal combustion engine vehicles, hybrid and plug-in hybrid vehicles), driving range is much greater. In addition, conventional fuels are characterised by higher energy density than batteries allowing more energy to be stored on board, and, thanks to a widespread refuelling infrastructure and very short refuelling times (compared to BEV recharging time), range is not a relevant issue.

Franke and Krems (2013b) provide evidence that charging patterns are not only associated with mobility needs (e.g. the need to participate in out-of-home activities) but also with what they call users' own *comfortable range* and *battery interaction style.* Their work is based on empirical data collected through interviews carried out amongst participants of the previously mentioned Berlin MINI-E trial. The data collection that was carried out in parallel with automatic monitoring of vehicle use included car diaries and charging diaries at various stages of the trials, along with in-depth interviews, "trip decision games" to assess the range buffers used by participants, and questionnaires to quantify the extent of users' engagement in controlling electric vehicles' battery state of charge (Cocron et al., 2011)

In a first study Franke and Krems (2013a) analyse the psychological dynamics of electric vehicle users' interaction with the limited mobility resources provided by battery electric cars. Drawing on control theory and self-regulation of behaviour (Carver and Scheier, 2001) they develop and test a conceptual framework (Figure 6) based on the idea that users manage range resources as a control task. In their framework, users adopt adaptive control of range resources based on range reference value. In particular they propose that the appraisal of the range resources depends on what they call "comfortable range": i.e. a range comfort zone within which an EV user is not affected by what is typically referred to in the popular press and scientific publications about EV use as range anxiety (Nilsson 2011).

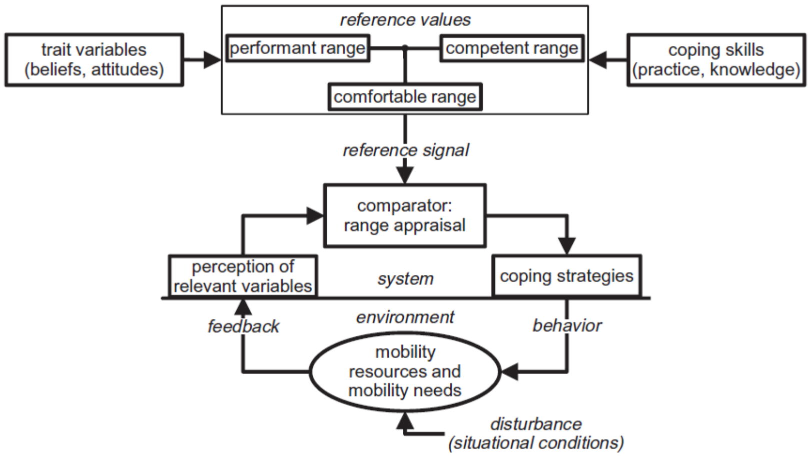

Figure 6 Adaptive control of range resources, reproduced from (Franke and Krems, 2013a). This image has been reproduced with the permission of the rights holder, Elsevier.

Comfortable range is related to the idea of a preferred range safety buffer. This could, for instance, be quantified as a fraction of the difference between the available range and the anticipated driving distance relative to the latter. The lower the preferred safety buffer the larger the range comfort zone, hence the larger the comfortable range. Comfortable range is affected by the typical range that is usually achieved (termed “performant range”) and the maximum range that is perceived as being achievable. According to the authors’ conceptual framework, if the available range differs markedly from the comfortable range the appraisal may be “fast and automatic”. Instead, if the available range and comfortable range values are close to each other, then users would adopt a more deliberate evaluation considering the performant and competent range. The coping strategies enacted by EV users to manage the limited range, amongst which is the charging strategy, would be informed by this range appraisal. For a sample of 40 EV participants in the MINI-E trial in Berlin they find that control beliefs[16] and other personal traits such as impulsivity and ambiguity tolerance are predictors of the three range reference values. They also find that measures of users’ self-

[16] Theory of planned behaviour “postulates that behaviour is a function of salient information, or beliefs. […]. Three kinds of salient beliefs are distinguished: behavioural beliefs which are assumed to influence attitudes toward the behaviour, normative beliefs which constitute the underlying determinants of subjective norms, and control beliefs which provide the basis for perceptions of behavioural control”. Control beliefs are those that affect behaviour based on the appraisal of the sources available. “The more resources and opportunities individuals believe they possess, and the fewer obstacles or impediments they anticipate, the greater should be their perceived control over the behaviour” (Ajzen, 1991).

appraisals of their competence in using electric vehicles, users' "subjective system competence", are positively related to the three range values.

In a later paper, Franke and Krems (2013b) analyse charging behaviour as a coping strategy in the part of the control loop framework they developed for EV users interaction with limited resources (Figure 7). They find that comfortable range and "user-battery interaction style" can explain a significant proportion of the variance in the average level at which trial participants initiate a charging event. The "user battery interaction style" is a qualitative classification of EV users based on how they decide to charge their vehicle. Users are classified based on their propensity to charge, a) when a specific safety margin is reached, or b) to charge (more often) any time there is the opportunity. Their empirical findings show that both comfortable range and user-battery interaction intensity are negatively related to the battery level at the start of a charging operation. Indeed, individuals with a larger range comfort zone will tend to exploit more fully the battery capacity, as well as individuals more prone to base their charging decision on safety buffers, since they are likely to have acquired a deeper understanding of the battery dynamics than those that make their charging decisions more opportunistically.

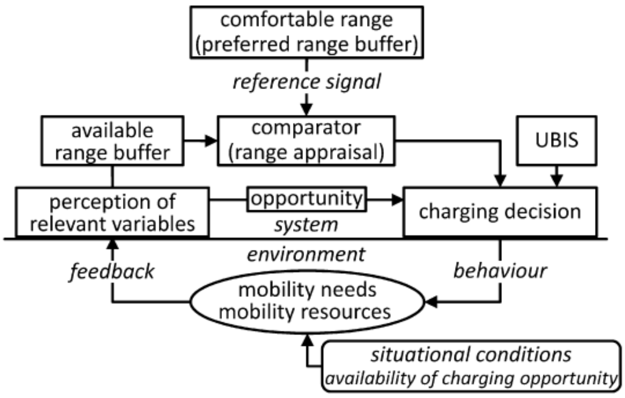

Figure 7 Charging decisions as a coping strategy in an adaptive control loop for range renounce management, reproduced from (Franke and Krems, 2013b). This image has been reproduced with the permission of the rights holder, Elsevier.

Franke and Krems' work exposes the relationship between user-battery interaction style, battery level and charge start and provides initial evidence for the heterogeneity in charging behaviour. This supports the intuition that the use of charging behaviour scenarios that simply assign a homogenous behaviour to all EV users may be misleading. The heterogeneity in user-battery interaction style should be interpreted in tandem with the average charging frequencies observed in trials. The low weekly frequencies observed in the trials discussed in subsection 3.2.1 may indeed also be a result of this heterogeneity and not only of low EV use levels amongst trial participants. Franke and Krems, however, do not attempt to test whether the user-battery interaction style has a significant explanatory power for charging frequency. Such a test could be performed, however, by using the EV charging and use data collected in the EV Berlin trial from instrumented home charging posts and EVs, for those participants subjected to user-battery interaction style profiling.

Franke and Krems' work also supports the idea that preferences in terms of battery level are related to charging decisions. Indeed, the concept of comfortable range could be interpreted from a microeconomic perspective as range or battery level preference under uncertainty. While Franke and Krems only consider the battery level as a trigger in the decision to start charging, however, it could be argued that the idea of battery level preference can be pushed further. In situations where the cost of the charging operation varies considerably at different charging opportunities due to static time-of-use pricing or other tariff structures (e.g. based on real time electricity costs), preferences in battery levels may not only affect the decision to initiate charging but could also affect the battery level that is achieved by charging; since trade-offs may take place between charging costs and the energy available in the vehicle battery (i.e. the range).

Franke and Krems' theoretical framework based on concepts such as "user-battery interaction" levels, "comfortable range", "competent range" and "performant range", indeed express features that may help the understanding of the underlying drivers of range appraisal and charging decisions. Arguably, however, it overcomplicates the decision making process. A simpler, but more rigorous, decision making framework is, in this author's view, necessary in order to make the step towards predictive models of charging behaviour. The influence of psychological traits and perceptions need not necessarily be sacrificed in such a model: for instance, a utility-based core, to describe the decision making process, can be extended to capture the effect of latent attitudes and perceptions (range reference values), and EV users latent classes (users' battery interaction styles). Furthermore, it could accommodate in a mathematically rigorous way the uncertainty that underlies the charging decisions (and determines "comfortable range" preferences) drawing from the broad literature on decision making under uncertainty: expected utility theory (EUT) or non-EUT theories, such as prospect theory (Kahneman and Tversky, 1979) and cumulative prospect theory (Tversky and Kahneman, 1992) which were developed to account for deviations from EUT observed in experiments.

Recently, an empirical model for PHEV individual charging choices that has some potential for charging choice forecasting purposes was developed by Zoepf et al. (2013), making use of revealed preference data from a pre-production Toyota Prius PHEV trial carried out between

April 2011 and April 2012 in the United States. Zoepf et al. use a random coefficients mixed logit model to model the occurrence of a charging operation at the end of a journey. The authors identify the following as significant explanatory variables: the current state of charge of the PHEV battery; the available time before the next journey; the distance travelled in the most recent journey; whether the journey was in fact a tour and the end time of the most recent journey. They also found a significant standard deviation in most of the utility coefficients. Zoepf et al.'s model has an interesting application in forecasting the occurrence of charging based on recent journey information. It cannot be used to model charging choices in response to various tariff structures, however, since the effect of electricity price either was not considered or, more likely, was not characterised by enough variability to allow the estimation of cost sensitivity. The significance of the standard deviation for the state of charge coefficients may suggest idiosyncratic preferences regarding available battery levels. Although the previous journey distance variable partially controls for the vehicle use variability, adopting the distance travelled as a usage indicator, the distance travelled since the previous charging event, or the energy consumed, might have given more confidence that variability in the state of charge indeed reflects taste heterogeneity, for available battery levels.

3.3 Conceptual framework

This section after providing a definition of charging choice and its dimensions presents how these are related to the dimension of activity-travel choices. It is highlighted in particular how the relation between charging choices and activity-travel timing choices is important modelling the response to demand side management (DSM) / demand response (DR) measures for charging.

3.3.1 The charging choice and its dimensions

The charging behaviour literature analysed in section 3.2 has highlighted the following:

- Electric vehicles (in real world trials) are not charged with a daily frequency;
- Battery levels triggers the decision to initiate a charging operation.

These two observations suggest that the level of available energy plays a role in the determination of the charging behaviour. Therefore this can be considered as an attribute characaterising alternative charging options in a charging choice. In fact the objective of the charging operation is to increase the level of available energy by a certain amount.

Given the current charging infrastructure scenario the amount of energy charged during the charging operation is determined simply by knowing the charging duration (i.e. start time and end time of the charging operation) because the charging power is usually fixed. In technological scenarios when charging services are provided at different costs depending on how fast the battery is being charged, however, electric vehicle users may trade off available energy, charging duration and costs.

In fact even in scenarios where the infrastructure itself does not provide the capability to control the charging power, electric vehicle users can in a way control how long it will take to recharge their EV, by delaying the start charging time, for example to take advantage of off peak electricity price (Schey et al., 2012). Delaying the charging start time means increasing the overall time elapsed from the arrival time at the charging facility to the time the battery has reached the desired level. Users may decide, for example either

a) to delay the charging start time in order to charge at lower prices, but possibly to lower energy levels (if they need to depart before the battery has reached the desired level); or
b) to delay the charging start time in order to charge at lower prices but charge to a higher level, with a charging duration that may induce a later departure with respect to their preferred departure time; or
c) to avoid delaying the charging operation and pay more for a higher battery level so as to ensure a swifter vehicle availability in order to leave at the preferred departure time.

In more advanced scenarios ("smart charging scenarios") communications between the electric vehicle charger and the electricity supplier (the charging service provider, CSP) may be allowed. In this case EV users may simply choose the target battery level they want to achieve and the time by when this should be achieved, based on prices communicated by the CSP. In turn the CSP will satisfy this request by delivering the energy according to a schedule that facilitates its operations and contributes to minimising its costs (Sundstrom and Binding, 2011). Clearly, tariffs for the charging service will tend to favour charging settings that allow greater flexibility for the CSP in the definition of charging schedules as the CSP objective is the optimisation (cost minimisation) of its operations. It is evident that the longer the time the vehicle is connected to the grid, the more flexible the charging operation can be, because there is more leeway in defining the charging schedule, within the limit of the maximum charging power. On the other hand, if the EV electric vehicle user wants to have the vehicle charged as fast as possible, the CSP must deliver the energy continuously at the maximum charging power.

Considering the potential settings for the charging operation described above, we can describe the charging choice at a given charging opportunity in terms of:

- charging start time preference;
- charging end time preference;
- and preference in available energy at the end of the charging operation.

The charging operation start time, can only be coincident with or delayed with respect to the arrival time at the charging facility. Therefore, from the electric car driver perspective, the charging operation could be considered as starting at the vehicle arrival time, regardless when the actual energy transfer may take place. In this perspective both smart charging and conventional charging could be represented only as a two dimensional choice, where the two dimensions are: the final battery level and the time it takes to achieve it, since the arrival at the charging facility. This time indeed represent the “effective” charging duration. Hereafter we simply use the term charging duration (or charging time, CT) to refer to this quantity.

Figure 8a shows the concept of charging choice as proposed in this study. At a given charging opportunity, EV users choose the energy they want available at the end of the charging operation as well as the charging duration. Note that in the figure, the available energy is presented in as percentage of the total battery capacity, state of charge. The charging choice space is constrained by the characteristics of the electric vehicle and the charger, which determine the (maximum) charging power. The other (obvious) constraint is the maximum battery capacity (SOC=100%). A particular charging alternative is represented by a point in the feasible charging space, thus characterized by the following attributes:

- available energy after charging,
- the charging duration

An additional attribute is the cost of charging, which will depend on the electricity tariff: Individuals facing a charging choice will trade-off between these attributes depending on the electricity tariff structure. For instance, a user may decide to allow a longer charging duration to take advantage of lower electricity price periods according to a static time of use tariff (Figure 8b). On the other hand, a user may choose CT and SOC according to an offer that is signalled by his/her charging service provider, exploiting the communication capabilities of smart grid systems. The charging service provider, within the technological limits and the constraints posed by the user request (Figure 8c), will establish the actual charging schedule (Figure 8d).

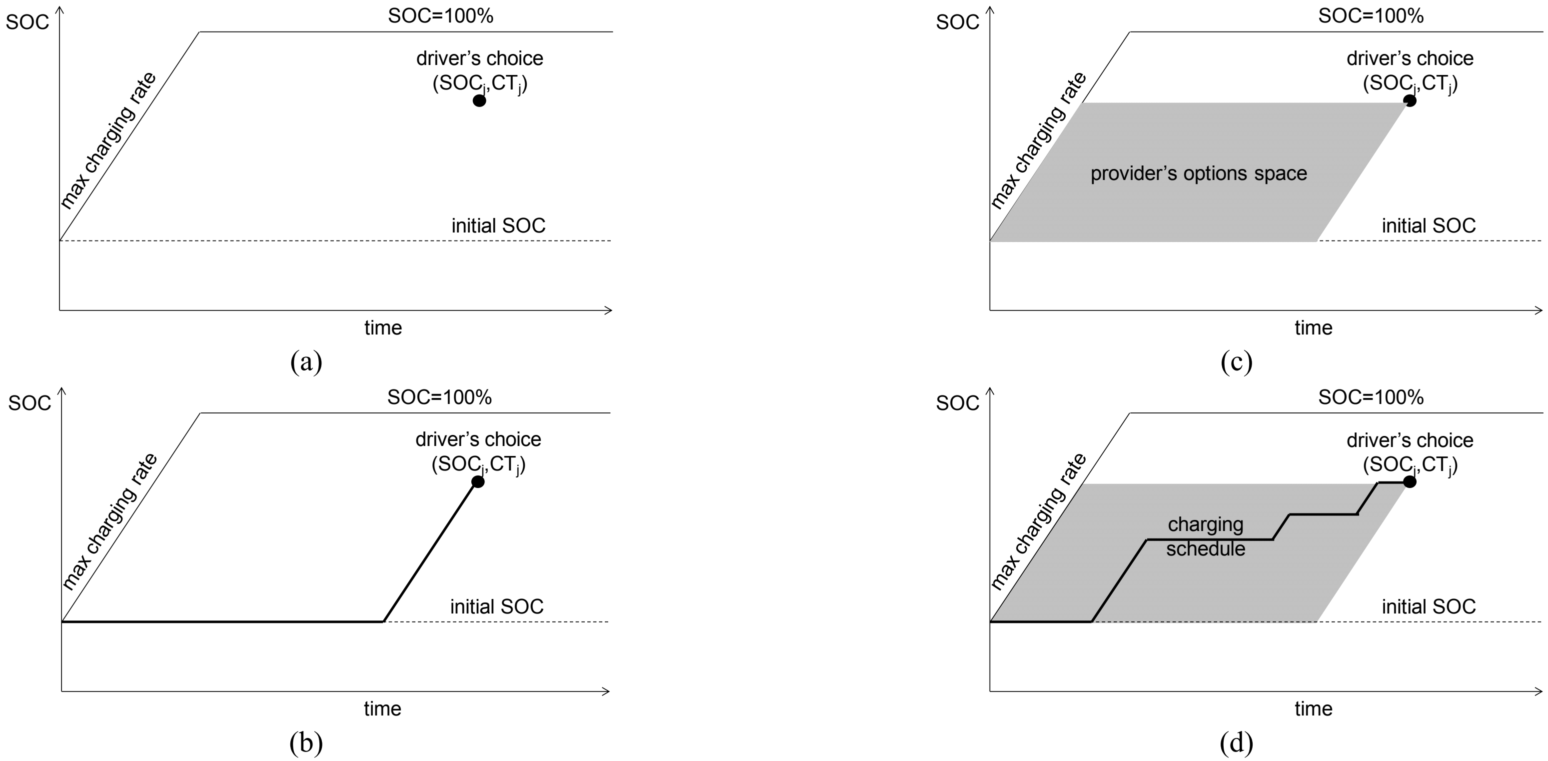

Figure 8 Conceptual view of a charging choice at a given charging opportunity. (a) shows the dimensions it entails; (b) shows a possible charging schedule underlying charging choice, where an EV driver delays the charging start time to take advantage of lower electricity prices; (c) shows the space leeway available to a charging service provider underlying the charging choice; (d) is an example of charging schedule resulting from accepting external control of the charging operation by a charging service provider

3.3.2 Interrelation between charging and activity-travel patterns dimensions

Activity-travel behaviour and charging behaviour presents manifold interrelated dimensions. Charging duration and energy available after charging were identified above as the two characteristic dimensions of the charging choice. These two decision variables are intertwined with the dimensions of activity-travel pattern choices, either directly or indirectly. Table 1 shows the potential relationships between the charging choice dimensions and the activity-travel choice dimensions.

Table 4 Relations between charging choice dimensions and activity-travel choice dimensions

	Activity type	**Activity timing**	**Activity duration**	**Activity location/Travel destination**	**Travel mode**	**Departure time**	**Travel route**
Available energy				✓	✓		✓
Charging duration		✓	✓			✓	

Activity location and available energy are related as there may be trade-offs between the location where an activity is carried out and the energy (i.e. the available range) a driver may want to have available at departure, in order to comfortably undertake the journey between the current and the next charging opportunity.

Charging and mode choices are also potentially related. Under a particular electricity tariff structure, at a charging opportunity it may be more convenient for a driver to leave the EV on charge and use another travel mode to reach a destination rather than charging to a level allowing a comfortable drive to the target destination (and beyond, if the destination does not provide a charging opportunity);

Route choice may also potentially occur based on range considerations; therefore the available energy dimension of charging choice is related to route choice.

The charging duration may have direct impacts on the timing dimension of activity-travel choices: the charging duration may require longer dwell times at a location, thereby inducing schedule delays, i.e. variation with respect to preferred activity timings. For example, a driver may be induced by a lower unit cost of energy, resulting from a specific tariff structure of the charging service, to remain at a location longer than the normally preferred time.

The choices across activity and travel dimensions are related to each other. In fact, due to technological constraints, charging choice dimensions may be interrelated as well. This leads to hypotheses of "indirect effects" (not explicitly expressed in Table 1) between charging dimensions and activity-travel dimensions. Here, the phrase “indirect effects” refers to the effects on an activity-travel dimension resulting from a charging decision that has as an intended effect along another activity-travel dimension. Such indirect effects are the typical result of the coupling of two choice dimensions induced by constraints. The most obvious example is spending more time in an activity in order to let the EV charge for a longer time to a comfortable battery level for travel. This may happen because it is not possible to charge faster. Anecdotal evidence for this is provided in in-depth interviews associated with electric vehicle trials. For example Graham-Rowe et al. (2012) report the experience of a user extending his working hours in order to charge his BEV to return home comfortably. In this case the schedule delay is a “by-product” of a charging decision intended in the first place to enable reaching a destination (home, in the example), induced by the characteristics of the charging infrastructure. These indirect effects, mainly attributable to physical constraints, induce trade-offs between the space-related and the time-related activity-travel choice dimensions that are expressed though charging choices, i.e. trade-offs between available energy and charging duration.

Amongst these interactions, the relation between charging and activity-travel timing choices is of particular interest in modelling the effect of DSM/DR measures (e.g. time of day pricing), and in general the tariff structures of the charging services for (CSP). DSM/DR measures are especially aimed at controlling the time of-day-load profile from EV charging. Therefore they have purpose to influence the timing and duration of EV availability for charging, or discharging when vehicle to grid operations are allowed (see section 1.4). Instead whether an EV is driving or parked (possibly at a location with charging facility) during the day is determined by the decision of the EV driver to participate to (in and out of home) activities at various times of the day.

Therefore the response to of DSM/DSR measures and tariff structures from charging services could be usefully analysed considering in particular the relation between charging choices and activity-travel timing choices. The modelling framework that this study develops here is specifically aimed at analysing precisely this relation.

It is recognised that also the other activity-travel dimensions are of great importance in determining EV load profiles and the response to demand management (e.g. activity location choice by determines the spatial patterns of EV charging). However limiting the scope of the analyses to activity-travel timing and charging choices is necessary due to resource constraints for this PhD research.

3.4 Modelling framework

The modelling framework introduced in this section essentially extends the traditional random utility activity-travels timing choice models to account for the utility of charging while an electric vehicle is parked at a location where a charging opportunity is available.

Before presenting the extended framework, approaches to time of day choice modelling are briefly reviewed below.

3.4.1 Time of day choice modelling

Time of day choices of travellers are important for transport planning mainly because in dense urban areas they are central to the generation and dissipation of congestion waves (Mahmassani, 2000). Transport analysts have been working on understanding the determinants for these decisions for several decades in order to devise demand side strategies that serve to spread peaks in demand. This is vital for improvements in the operational reliability of transport networks in urban areas. Demand side strategies may in fact avoid resorting to capacity increases, especially in situations in which this may not be physically, economically or politically viable. Moreover, they allow other issues associated with congestion externalities to be tackled: particularly poor urban air quality and the health risks that this is associated with (Levy et al., 2010).

Most of the studies analysing the choice of the time of travel are based on the concept the individuals have a preferred time of travel and moving away from that causes disutility. In particular the first important contribution for this view is the model of Vickrey (1969), in which it is assumed that individuals choose their time of travel as result of a trade off between travel time and a measure of early arrival and late arrival to work (Vickrey's studies only commuting trips). The measures of early arrival and late arrival are schedule delay early (SDE) and schedule delay late (SDL) defined as follows

$$\begin{aligned} SDL &= \max(t_d + TT(t_d) - PAT, 0) \\ SDE &= \max(PAT - (t_d + TT(t_d)),0) \end{aligned} \tag{3.1}$$

where t_d is the departure time, $TT(t_d)$ is the departure time dependent travel time and PAT is the preferred arrival time. The choice of travel time is treated in standard microeconomic perspective as a result of the maximisation of the following utility function

$$V(t_d) = \alpha TT(t_d) + \beta SDE(t_d) + \gamma SDL(t_d) \quad (3.2)$$

All the model parameters α, β and γ are assumed to be negative since individuals derive disutility for longer travel times and for departure times that are shifted from the preferred one, whether earlier or later. This model assumes that travellers trade-off travel time and schedule delays, i.e. depending on the relative magnitudes of the marginal utilities, and that the optimal choice may result in accepting an earlier departure in order to reduce the travel time.

Vickrey's theoretical model was then reformulated and estimated empirically in a discrete choice framework using revealed preference data by Small (1982), who again considers only the trade-offs between travel time and schedule delays. Small's (systematic) utility function also considers an additional term to capture the jump in utility in the presence of a delay.

While the models by Vikery's model and by Small's model consider only time of day choice, later studies have combined time of day with other choices. Mannering (1989), Arnott et al. (1990), Mahmassani et al. (1991), and Khattak et al. (1995) have developed models for jointly analysing travellers' time of day ad route choices. Hendrickson and Plank (1984); Bhat (1998a); Bhat (1998b); de Jong et al. (2003); Hess et al. (2007) and Lizana et al. (2013) have jointly studied the choice of travel timing and mode. In other cases, the choice of time of travel has been studied in conjunction with choice of activity timing, for example by Polak and Jones (1994); Wang (1996); Ettema et al. (2004) and Ettema et al. (2007).

Moreover, while the models by Vickrey and Small have considered only tradeoffs between travel time and schedule delays, later studies have considered also other sources of tradeoffs: namely travel reliability and travel costs. The idea that travellers trade between travel times, schedule delay and charging costs is at the base of road pricing schemes. A review of studies considering the effect of travel time reliability is provided by Bates et al. (2001). Of those explicitly including travel costs, the majority were developed to analyse the effect of time-of-use road pricing (see for example, Polak and Jones, 1994, de Jong et al., 2003, Arellana et al., 2013).

Amongst the studies analysing the effect of price-based traffic management policies, some departed for the original trip based approach of Vickrey and Small to consider a tour-based perspective. Polak and Jones (1994) developed a theoretical framework for the simultaneous choice of the timing of the outbound and inbound legs of home-based tours. The advantage of a tour-based approach to time of travel choice is that it allows the explicit consideration of "the linkage between timing decisions of journeys within an overall activity pattern" (Polak and Jones 1994). The basic idea is that a traveller undertaking a daily commute maximises the utility that he derives from spending time on:

- home activities before the outbound journey,
- travelling to their destination,
- activities (work) at destination,
- travelling back home,
- and home activities after the inbound journey.

The utility of activities including travelling is time dependent, intrinsically and because of scheduling constraints. It also depends on the duration. In their paper Polak and Jones establish the link between outbound and inbound legs and the scheduling of activities at home and out of home. To represent the intrinsic preference for activity timing Polak and John use marginal utilities for activity participation in continuous time. Thus they represent the utility U^Athat an individual derives in taking part in an activity, in terms of its time dependent flow rate $u^A(t)$ drawing from Winston's theory on timing of the economic activities (Winston, 1982):

$$U^A(t^A, T^A) = \int_{t^A}^{t^A+T^A} u^A(\tau)d\tau \tag{3.3}$$

where t^A is the activity start time and T^A is duration.

Polak and Jones derive then the utility of a (two leg) home based tour as sum of individual contributions: the utility attained by spending time at home before travelling (starting from midnight); the (dis-)utility from travel at destination D, the utility from spending time at destination, the utility from travelling back home and the utility from spending the rest of the available time T, (e.g. 24 hours), time at home.

$$\begin{aligned} U &= \int_0^{t_{out}} u^H(\tau)d\tau + u^{TT}TT_{out}(t_{out}) + \int_{t_{out}+TT_{out}}^{t_{out}+TT_{out}+T_D} u^D(\tau)d\tau \\ &\quad + u^{TT}TT_{in}(t_{out}) + \int_{t_{out}+TT_{out}+T_D+TT_{in}}^{T} u^H(\tau)d\tau + U_G(G \end{aligned} \tag{3.4}$$

where: the $u^H(\tau)$ is the utility flow rate from spending time on home activities; u^{TT} is the utility flow rate (assumed constant) from spending time travelling; $u^D(\tau)$ is the utility flow rate from spending time at the destination, t_{out} is the departure time of the outbound leg, which is also equal to the time spent at home, from midnight, before departure, T_D is the time spent at the destination; TT_{out} and TT_{in} are the respective travel times. U_G is the utility from consumption of the generalised good G (assumed to be independent of time).

Travellers maximise U by choosing t_{out}, T_D and G subject to the budget constraint (the time constraint is already implied by the integral limits):

$$c_{out} + c_{in} + pG = Y + wT_D \tag{3.5}$$

where c_{in} and c_{out} are travel costs, p is the unit price of G, Y is an unearned income and w is the wage rate (which is multiplied by T_D since Polak and Jones consider specifically a home based tour to work).

They then derive an expression for the indirect utility by:

- Linearising the expressions of the utilities from activity participation, by using first order Taylor expansions around reference timings (e.g. those form a tour observed in a traveller's travel diary);
- Substituting first order Taylor expansions of the utility attained in home and destination activities into the Lagragian of the optimisation problem above.

Finally, they obtain an expression of the following form for the indirect utility of a tour:

$$V = \beta(t_{out} - t_{out}^*) + \gamma(T_D - T_D^*) + \delta(TT_{out} + TT_{in}) + \eta(c_{out} + c_{in}) \tag{3.6}$$

where t_{out} is the departure time of the outbound leg, T_D is the time spent at destination; TT_{out} and TT_{in} are the respective travel times and c_{out} and c_{in} are the inbound and out bound travel costs respectively. The starred quantities are the respective quantities in an observed tour. In the expression above we can identify in the first term a schedule adjustment, in the second term an adjustment in activity participation at destination, often named participation time penalty Hess et al. (2007). The meaning of such an expression is that travellers "trade-off schedule delay against participation time, when adjusting to changes in travel times and costs". Polak and Jones approach was then followed in other empirical applications by de Jong et al. (2003) and Hess et al. (2007).

Polak and Jones's model was further expanded by Ettema et al. (2007) in order to disentangle intrinsic time of day preference from the effect of scheduling constraints and to take into account satiation effects in the utility attained from activity participation. Ettema et al. (2007), in order to express the intrinsic preference to take part in a specific activity at a specific time of day use a nonlinear (bell-shaped) functional form for the time of day dependent marginal utility of activities. This bell-shaped marginal utility means that there is a specific time of day in which the marginal utility for taking part in that activity is at a maximum. The functional form they choose for the marginal utility (that of a Cauchy distribution) has a closed form integral, so that they do not need linearization to express the utility. To express satiation effects they use the logarithm of the activity participation time, so that the longer the time spent in an activity, the lower the marginal utility the individual attains from it. Finally, in order to capture the effect of scheduling constraints, Ettema et al. (2007) use schedule delay terms as in Small's approach. These three contributions to the utility attained from activity participation are assumed to be additive.

They thus obtain the expression of the utility for activity participation as:

$$V^A(t^A, T^A, t^{*A}) = \int_{t^A}^{t^A+T^A} M^A(\tau)d\tau + \eta_i \ln(T^A) + \gamma_i^e SDE(t^{*A}) + \gamma_i^l SDL(t^{*A}) \tag{3.7}$$

where $M^A(\tau)$ is the marginal utility for participating in an additional instant to activity A, T^A is the duration of the activity, t^A the activity start time, $SDE(t^{*A})$ is the early schedule delay with respect to a preferred start time t^{*A} of the activity, $SDL(t^{*A})$ is the late schedule delay with respect to a preferred start time t^{*A}.

The expression above is then used in a formulation that expresses the utility attained in an activity-travel as a sum of contributions from activity participation and contributions from the time spent travelling.

It should be pointed out that all the tour-based models mentioned have been estimated using SP data, whereas, there are examples of trip-based models in which the estimation was also based on revealed preference data. Apart from the first RP study by Small (1982), more recent work by Lizana et al. (2013) estimates a trip timing model jointly using SP and RP data from a recent survey carried out in Santiago, Chile (Arellana et al., 2013). Furthermore, often, instead of calculating the schedule delays with respect to the preferred arrival time (or departure time), since this needs to be explicitly asked of survey respondents, observed arrival (departure) times are used as a reference. This approach has been questioned by Bates (2008b) because it is inconsistent with the Small-Vickery method. When observed timings are used as a reference, the utility of several scheduling alternatives is relative to the status quo. This may not be representative of the preferred condition; therefore a schedule delay may not necessarily cause disutility. The status quo is likely to be the result of a series of seamless adaptations in travellers' interlinked activities, however, and therefore a change is very likely to cause a disutility, resulting in disruption to current behaviour. This is demonstrated by the consistently negative estimates in schedule delay parameters obtained in studies using observed travel timings as reference points in the definition of the schedule delay terms.

In the next section for the formulation of the model for joint EV use scheduling and charging choices, we adopt delay/participation time penalty formulation, as the novelty of the present work is intended to be the joint analysis of charging and activity timing choices. The nuances introduced by Ettema et al. are for the sake of simplicity, avoided in the present treatment.

3.4.2 Joint model of charging and activity travel timing choice

In order to jointly analyse EV charging and travel decisions, i.e. to study EVUSC decisions, we use a modelling framework that embeds charging choices in activity and travel timing decisions. To achieve this we make the following broad assumptions:

- Individuals make their charging decisions once they arrive at a location where charging is available.
- They decide when to depart jointly with the charging decision.
- This joint decision refers to a portion of an EV driver's schedule delimited between charging opportunities.
- The evaluation of a charging alternative is based on three attributes that characterise it: available energy at the end of charging, charging duration and charging costs.

With these assumptions individuals make their charging choices only considering their current available energy and the energy required until the next charging opportunity. Their choice is thus modelled as myopic, because it does not entail consideration of the characteristics of all charging opportunities within a given time framework. A myopic choice, however, appears consistent with the view of charging behaviour as a coping strategy resulting from range appraisal (which may occur at the end of a journey), as conceptualised and tested by Franke and Krems (2013b). Nevertheless, this is a simplification if one considers situations in which a variety of charging opportunities with different electricity prices were available to an electric vehicle driver aware of the price differences across charging opportunities.

Figure 9 shows the activity-travel episodes which EVUSC choices refer to Each choice refers to a charging opportunity and the activity travel episode before the next charging opportunity, in the figure such episode in comprised between vertical dashed lines.

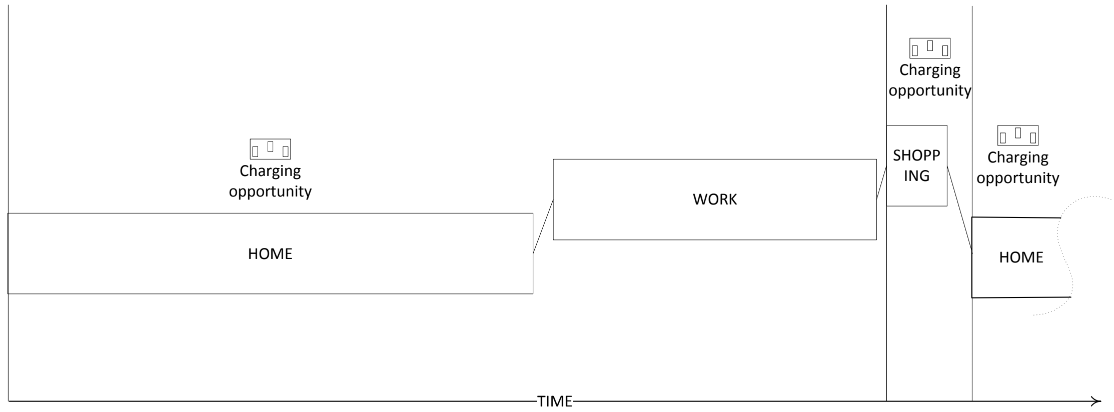

Figure 9 Charging opportunities and activity-travel episodes. In the present analytical framework each choice refers to a charging opportunity and the activity travel episode before the next charging opportunity. These are comprised between two consecutive vertical dashed lines

The EVUSC's utility can then be thought as the sum of two separate terms: one referring to the charging operation and one referring to the corresponding activity-travel episode.

$$U_i = U_i^{charging\ option} + U_i^{activity-travel\ episode} \quad (3.8)$$

where the subscript i represents a discrete charging setting and travel timing option.

We specify the systematic utility of the EV activity-travel episode in terms of the timing and duration of its constituents, adopting a schedule delay formulation.

The activity-travel episode we consider here need not be a tour, but simply an activity-trip chain starting with a (stationary) activity, in a location with an available charging facility. Thus, the systematic utility of the activity travel episode is the given by:

$$V_i^{activity-travel\ episode} = \beta_{SDL}SDL_i + \beta_{SDE}SDE_i + \beta_{DL}DL_i + \beta_{TT}\sum_{k=1}^{k=N_a+1} TT_{ki} + \beta_C \sum_{k=1}^{k=N_a} TC_{ki} + \sum_{a\in A}\left(\beta_{PD,a}PD_{ai} + \beta_{PI,a}PI_{ai}\right) \quad (3.9)$$

where SDE_i and SDL_i are outbound early and late schedule delays respectively with the respect to the preferred departure time for the first trip in the chain. DL_i is a dummy variable capturing the jump in utility if schedule delay late is different from zero, (this term is also present in Small's specification). PD_{ai} and $PI_{ai}$are the activity participation penalties for activities a undertaken within the activity-travel episode, after departure. In particular PD_{ai} is a decrease in participation time, PI_{ai} and an increase. Schedule delays and participation penalties are here defined as it follows (Hess et al., 2007).

$$\begin{gathered} SDL = \max(t_d - t_d^*, 0) \\ SDE = \max(t_d^* - t_d, 0) \\ PD = \max(T^* - T, 0) \\ PI = \max(T - T^*, 0) \end{gathered} \quad (3.10)$$

where t_d is a generic departure time and T a generic activity duration. The starred quantities identify the respective preferred departure time and duration.

TT_{ki} and TC_{ki} are the travel times and the non-fuel travel costs of K trips in the chain. β_X, where the subscript X is generic, are model parameters and represent the marginal utilities constituting the marginal utilities. Note that schedule delays specific to trips following the first cannot be included in a model in which activity participation penalties are specified, because the schedule delay associated with the first trip in the chain and the activity participation penalties already account for all the changes in timings and durations, with respect to the preferred timings of the activity travel episode.

The systematic utility of a charging option depends on the energy available after charging, that is the battery capacity C times the state of charge SOC of the battery at the end of the charging operation. It also depends on the duration of the charging operation, and on the charging cost. We specify linearly the utility attained by the available energy after charging:

:

$$V(E)_i = \beta_E(C * SOC_i) = \beta_E E_i \quad (3.11)$$

The component of the systematic utility depending on the charging duration has a more complex specification. Let T_i be the dwell time at the origin before the first trip of the activity-travel episode and CT_i the charging duration (recalling that we define the charging duration as the elapsed time between the arrival at the charging facility and the time the vehicle is charged to the desired battery level), T_i is therefore

$$T_i = T_0 + SDL_i - SDE_i \quad (3.12)$$

where T_0 is the dwell time at the origin with no schedule delays with the respect to the departure times form the origin. If the charging option does not induce a schedule delay (i.e. $T_i > CT_i$), then we express the contribution of the charging duration to the utility of the charging option as a linear function of the charging duration:

$$V(CT)_i{}^{no\ induced\ delay} = \beta_{CT} CT_i \quad (3.13)$$

This term expresses the (dis-)utility for the time elapsing until the vehicle is available with the chosen battery level. A negative parameter sign means that drivers benefit from having the vehicle available as soon as possible before the planned departure time, which can be interpreted as an option value for being able to depart earlier; if external unanticipated circumstances require doing so.

When $CT_i > T_i$, the contribution to the (dis-) utility of the charging duration is confounded with that of a schedule delay. Thus, the contribution of the charging duration to the total utility of the charging option is:

$$V(CT)_i^{induced\ delay} = \beta_{SDL} CISDL_i \quad (3.14)$$

where

$$CISDL_i = \max(CT_i - T_i, 0) \quad (3.15)$$

$CISDL_i$ is the charging induced schedule delay, amounting to the difference between the charging duration and the dwell time at the location where the charging takes place. The dwell time already includes possible delays from other sources. Therefore, the scheduling delay from the charging duration contributes to the (dis-)utility only when it causes a net schedule delay late contribution. If the departure time is already delayed for other reasons beyond the end of the charging operation, the charging duration will still contribute to the utility as early charging, even if the charging ends after the preferred departure time.

The systematic utility for the charging option can therefore be expressed as:

$$V_i^{charging\ option} = \beta_E E_i + \beta_{CT} CT_i * (1 - \delta_{CISDL_i}) + \beta_{SDL} CISDL_i + \beta_C CC_i \tag{3.16}$$

where CC_i is the charging cost and δ_{CISDL} is a dummy variable equal to one when a charging option does induces a schedule delay. This expression is therefore linear in E_i and nonlinear in CT_i. Nonlinearities in E_i can be tested in the estimation of the empirical model.

We then write the expression of the total utility for charging and timing alternative i for driver n as the sum of all systematic utility contributions plus a zero mean error term ϵ_{in}:

$$U_{in} = V_{in}^{charging\ option} + V_{in}^{activity-travel\ episode} + \epsilon_{in} \tag{3.17}$$

The expressions for the components of the expressions above were derived for a single electric vehicle driver, but, different drivers will have different travel patterns and also idiosyncratic preferences. The subscript n formally expresses this.

Specifying the error term as IID extreme value type I lead to the multinomial logit model (MNL). Recalling equation (2.1) MNLchoice probabilities, for EVUSC option i can be expressed as

$$\frac{\exp\,(V_{in}^{charging\ option} + V_{in}^{activity-travel\ episode})}{\sum_{k \in K_n} \exp\,(V_{kn}^{charging\ option} + V_{kn}^{activity-travel\ episode})} \tag{3.18}$$

where K_n is the choice set for individual n. This simple formulation is attractive, but it is encumbered by the independence of the irrelevant alternatives (IIA) property. IIA means that the addition of a new alternative to the choice set, or a variation in the attribute value of a non-chosen alternative, does not affect the relative odds between the other alternatives. This may be a limitation in the present case, since it implies the absence of an increased substitution rate between adjacent energy levels, (or adjacent charging durations, or adjacent departure times), compared to energy levels (charging durations, departure times) that are parted from each others. This means, that under IIA, for example, introducing a lower tariff to promote charging durations above 10 hours generates a proportionate decrease in the probability of a choice of a 10 hours charging duration compared to a 5 hours charging duration. We would instead expect disproportionate decreases. Despite this limitation, the MNL model's ability to empirically estimate utility parameters still provides an insight into the relative magnitude of the choice attributes allowing the identification of those amongst them that have stronger effects on the EVUSC choice. The relative magnitudes between available energy, charging duration; charging-induced schedule delay and charging costs, are of particular interest since they provide useful insights into how individuals may respond to stimuli in the form of different tariff structures for a charging service. The use of the MNL model for EVUSC choices is further discussed in Chapter 5 (section 5.2.3 and equation (5.4)), where empirical estimations of the modelling framework presented here are presented.

3.4.3 Modelling framework applied to a home based tour

The model presented in the previous section applies to the charging choice and timing choice of a general activity-travel episode consisting of a chain of trips and activity chains *following* the charging opportunity but *before* the next charging opportunity.

In order to better explain the meaning of the model presented above, we consider the specific case of a (two leg) home based tour, with home charging as the only charging opportunity (Figure 10), instead of a general activity-travel episode.

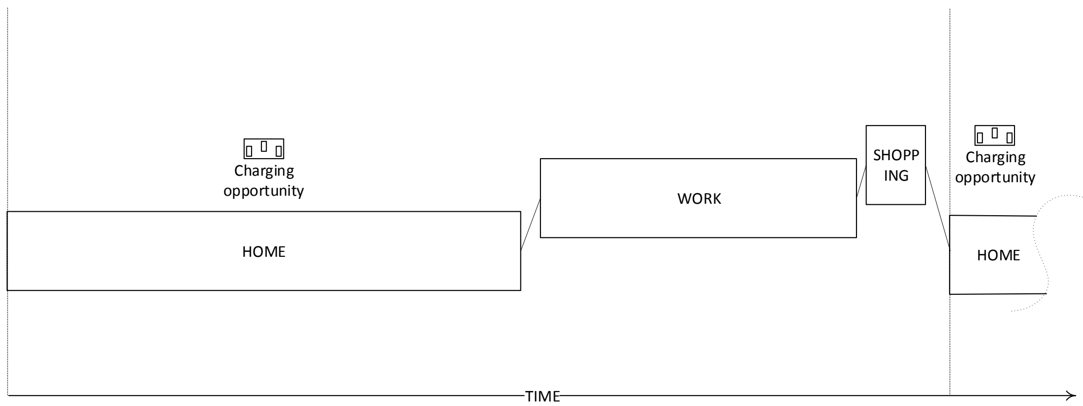

Figure 10 When only home charging is considered available, the unit of analysis becomes a home-based tour. This constitutes the setting used to develop the stated choice experiments in the ECarSim survey tool presented in Chapter 5.

In this case, utility for an EVUSC alternative can be written as:

$$U = \beta_{SDL}SDL + \beta_{DL}DL + \beta_{SDE}SDE + \beta_{PI}PI + \beta_{PD}PD + \beta_{TT}(TT_{out} + TT_{in}) + \beta_{SDL}CISDL + \beta_{CT}CT * (1 - \delta_{CISDL}) + \beta_E E + \beta_{COST}(TC_{out} + TC_{in} + CC) + \varepsilon \quad (3.19)$$

where the subscripts i and n indicating the EVUSC alternative and an individual electric vehicle driver are omitted for brevity; and

- SDL is a non-charging induced schedule delay with respect to the preferred (or an observed) departure time;
- DL is a dummy capturing the jump in utility when there is a schedule delay late;
- SDE is a schedule delay early with respect to the preferred (or an observed) departure time;
- PI and PD are activity participation penalties for the activity at the tour destination, namely a participation time increase and a participation time decrease respectively;
- TT_{out} and TT_{in} are travel times for the outbound and inbound leg of the tour;
- CT is the duration of the charging operation (charging duration, or charging time in brief);
- $CISDL = \max[CT - (T^H + SDL - SDE), 0]$ is a charging-induced schedule delay late[17], where T^H is the dwell time at home without schedule delays in departure time.
- δ_{CISDL} is a dummy equal to one when $CISDL > 0$
- E is the available energy stored in the electric vehicle battery after charging;
- TC_{out} and TC_{in} are non-fuel travel costs for the outbound and the inbound leg respectively;
- CC is the cost of the charging operation (charging cost in brief);
- β_X, (where X is a generic subscript), are utility parameters.
- ε in an error term.

[17] A charging option before departure can lead only to schedule delays late, while a "charging induced schedule delay early" is meaningless. The reason why SDL and $CISDL$ are expressed separately is to highlight the fact that the (dis-)utility for charging duration is perfectly confounded with the disutility for a schedule delay only when it is the cause of a late departure. When the charging operation ends after the preferred departure time but before a departure time delayed for other reasons (e.g. to avoid a time of day congestion charge), the dis(-utility) for charging duration is still expressed in terms $\beta_{CT}CT$.

The meaning of the expression above is that EV drivers, when planning their EV use, adjust departure times from home, and activity participation at their destination, by taking account of travel time and travel cost changes, as conventional car drivers do. They will also, however, choose charging durations and available energy levels by responding to charging cost. EV drivers may also respond to charging costs by choosing charging durations that are longer than the optimal time spent at home under a specific travel cost scenario, i.e. they may choose to accept a charging induced schedule delay.

The use of a home-based tour version of the model is also amenable to empirical estimation making use of home stated choice experiments. These, in fact, can be designed specifically to estimate the salient parameters of the charging choice, using as a hypothetical situation the choice amongst alternative charging options upon an EV driver's arrival at home, before undertaking his/her next tour. Chapter 4 details the development of a survey tool in which choice experiments are designed for this exact purpose.

3.5 Summary and contributions

The present chapter first reviewed recent studies defining and characterising charging behaviour. The review of real world charging behaviour studies shows that some of the assumptions of the charging behaviour scenarios typically adopted for modelling charging profiles do not hold. In particular, the evidence from trials challenges the typical assumption that electric vehicle users charge at any opportunity given the availability of infrastructure. This assumption particularly underpins the basic reference charging behaviour scenario referred to in the literature as "uncontrolled charging". Other scenarios, such as off-peak or delayed charging, which essentially just constrain the reference scenario also imply this assumption that charging will take place when evening and off-peak charging opportunities are available. If the weekly charging frequency levels revealed in EV trials do not only reflect EV use frequencies, but also preferences in EV range management strategies, then charging scenarios may overestimate the amplitude of peaks in EV charging load. Real world charging behaviour studies are merely descriptive and only some very recent works have started attempts to deepen the understanding of the charging behaviour or modelling making use of empirical data.

Following the review, the actual contributions of the chapter were presented. This consisted in the development of an analytical framework to analyse charging choices embedded within activity and travel timing decisions. Such framework is an extension of a traditional activity-travel scheduling modelling framework based on schedule delays and participation time that includes the contribution of the utility derived from charging when a charging opportunity is available. This analytical framework allow modelling the potential impact of charging demand side management policies (pricing in particular) on both charging pattern and timing of travel. While this is feasible using integrated modelling tools such as the MatSim-PMPSS described in the previous chapter; the framework presented here explicitly allows tradeoffs between the energy made available by a charging option and the timing of the activity-travel schedule that follows. This enables capturing potential effects of managing the limited range resource characterising electric cars with tour timing, as well as modelling the effect of pricing policies on both charging demand and timing of travel.

Moreover, the analytical framework presented is based on a novel conceptualisation of charging choice as a two dimensional choice whose main features are the time elapsed from the arrival time at a charging facility and the energy made available at the end of the charging operation. This conceptual model is simple but comprehensive because it allows a description from the user perspective of the charging choice both in current charging scenarios and in more advanced smart charging scenarios when the electric vehicle user may have options to choose amongst alternative offers from a charging provider aimed at incentivising charging choices so as to optimise its operations.

Chapter 4
THE *ECarSim* SURVEY

4.1 Overview

The generic utility function for the joint choice of home charging option and tour timing is reproduced here from Chapter 3 as reference:

$$
\begin{aligned}
U &= \beta_{SDL}SDL+\beta_{DL}DL+\beta_{SDE}SDE+\beta_{PI}PI+\beta_{PD}PD \\
&+\beta_{TT}(TT_{out}+TT_{in})+\beta_{SDL}CISDL+\beta_{CT}CT*(1-\delta_{CISDL})+\beta_{E}E \\
&+\beta_{COST}(TC_{out}+TC_{in}+CC)+\varepsilon
\end{aligned}
\tag{4.1}
$$

where the terms in the expression above are defined in Chapter 3 subsection 3.4.3.

The utility parameters for travel time (β_{TT}), schedule delays (β_{SDL}, β_{DL} and β_{SDE}) and activity participation penalties (β_{PI} and β_{PD}) can be potentially estimated using existing time of travel choice surveys such as that collected for the London APRIL model (Bates and Williams, 1993, Polak and Jones, 1994), or the regional PRISM model in the West Midlands of UK (RAND Europe, 2004). The estimation of the marginal utilities of the target battery level and of the charging duration, however, requires information that is not available in existing datasets. Ideally, we need a dataset that enables us to explore the trade-offs between the attributes defining the tour timing portion of the utility and the attributes defining the utility of a charging option. This chapter, therefore, describes the data collection tool that was developed in order to explore trade-offs between target battery level, charging duration, charging cost and charging induced schedule delay late.

In essence, the objective of this chapter is to present the approach that was adopted to collect data enabling the estimation of β_E, β_{CT}, β_{SDL}, β_{COST}. The data source for our model estimation is a stated response (SR) survey, because revealed preference (RP) data on electric vehicle use is scarce, not readily accessible and in general does not present enough variability in electricity price for charging and in average charging power to allow the identification of the relevant parameters in our model. The use of RP data (e.g. from electric vehicle trials) together with this data, however, would allow some mitigation of the typical drawbacks of SR data, i.e. the potential biases arising when individuals are confronted with hypothetical situations. Although RP data is not used in this instance, Chapter 8 concludes this thesis by suggesting that further work should consider such joint RP-SR model estimation.

The present chapter is structured as follows:

- Section 2 provides an overview of the possible approaches to collect data using stated response methods;
- Section 3 describes ECariSim the survey methods finally developped;
- Section 4 describes one of the two choice experiments design part of ECarSim;
- Section 5 describes the second choice experiment of ECarSim;
- Section 7 describes the insight gained for plitoting the survey tool, and what changes were implemented for the full scale survey administration;
- Section 8 describes the sampling and survey administration strategy;
- Section 9 presents the characteristics of the collected responses.

4.2 Stated response methods

The lack of availability of RP data on EV use forces a reliance on stated response data, which must be obtained by designing stated response experiments.

SR methods in the context of electric vehicle use charging behaviour present two major challenges.

Firstly, most drivers in the UK (and indeed elsewhere) have no experience of (regular) use of an electric car, while they have an extreme familiarity with using conventional cars, which are substantially different. Turrentine et al. (1992) and Kurani et al. (1996) criticise the use of traditional stated preference surveys in electric vehicle market studies precisely for this reason: the asymmetry in experience produces biases in the evaluation of some vehicle attributes (range in particular). In the context of eliciting EV use and charging behaviour when charging demand management strategies are in place, hypothetical situations take respondents a step further away from their usual experience. In fact, they require the respondents to imagine how best to accommodate the charging operations within their travel patterns when such operations may entail variable costs (due, for instance to the tariff structure for the charging service).

Secondly, although the response model developed in this research project focuses only on the timing dimension of the travel behaviour, interactions between mobility and charging behaviour are expected to be broader. Responses to hypothetical situations regarding the charging/travel patterns can therefore be complex and difficult to anticipate.

Two different kinds of SR techniques can partially cope with these challenges, and both have advantages and limitations. These techniques are stated preference (SP) surveys tailored on observed travel patterns of respondents, and stated adaptation surveys (SA). We briefly review the two options and discuss their application in our research.

Respondent tailored SP surveys - In the context of studying the potential response of travellers to road use pricing, stated preference surveys have been developed in which respondents are given a set of alternative options to their current journey, which are characterised by changes in travel costs, activity-travel timings and mode. Examples of surveys in which stated preference tasks take this form are the survey for the APRIL model for London (Bates and Williams, 1993, Polak and Jones, 1994), a Dutch survey (de Jong et al., 2003) and a survey carried out for the regional PRISM model in the West Midlands of UK (RAND Europe, 2004). In all three surveys the travel pattern unit considered is a tour, and respondents are offered alternatives to their current tour pattern. This kind of design based on an observed tour is intended to avoid alternatives that the respondents may find totally unfamiliar. Specific strengths of the SP approach are:

- Stated preference survey can be rigorously designed so that one can have a higher degree of confidence in obtaining reliable estimates for the model parameters, than using data from complex stated adaptation games.
- SP survey choice experiments (stated choice experiments), as long as the number of alternatives and the number of attributes per alternative is kept reasonably low, can be perceived as a straightforward task.

However, in the specific context of charging choice, choice experiments that are designed in such a way as to be tailored to respondents' travel patterns may still be perceived as unfamiliar to respondents if these are non-EV drivers, because the charging process itself would be unfamiliar.

SA surveys - Simulation and gaming techniques (interactive SA) have been used to confront problems of analogous complexity to our current problem. Examples are: the "Household Activity and Travel Simulator" (HATS), which was developed to investigate the primary and secondary effect of transportation policies on household activity travel patterns (Jones, 1977); the "Car-Use Pattern Interview Game" (CUPIG), in which adaptation of household activity-travel patterns to increased fuel shortage scenarios are observed (Lee-Gosselin, 1995); and the previously mentioned PIREG,[18] in which EV purchase decisions are elicited after having guided the respondents through a process in which they were required to rethink their travel patterns under driving range constraints. In SA surveys, responses to hypothetical scenarios are open and both the choice outcome and the choice process are observed. They thus enable the researcher "to discover the responses that the respondent see as possible" (Faivre D'Arcier, 2000). The drawback of these methods is the high level of effort required from both the respondents and analysts due to the complexity of the tasks that the respondents have to undertake. This poses difficulties in achieving sample sizes that facilitate the estimation of statistically significant model parameters. The use of internet-based simulation tools, however, may allow increased sample sizes, partially mitigating this drawback. On the other hand, the advantage of a SA task in this specific context is that it allows a gradual adaptation on the part of a driver unfamiliar with the electric vehicle charging context, leading to possibly more aware decisions in the later stages of a stated adaptation game.

The two approaches have to a certain extent been combined in the past so as to exploit their respective strengths. Kurani et al. (1996) developed a multistage (and multiday) mail-based reflexive survey to analyse EV purchase decisions. In this survey the vehicle choice tasks were presented to the respondents after a series of other stages. These comprised: keeping a travel diary for a week and building a visualisation of the diary as a timeline; plotting their activity locations on a map and answering reflexive questions on the timeline, the map and travel related problems prompted by the revealed diaries. The reflexive part was intended to allow the respondents to analyse their travel patterns so that when undertaking their vehicle choice task, they were able to evaluate the vehicle characteristics with more awareness of the implications of these on their travel habits.

[18] See "Reliance on stated preference data" in section 2.3.1.

A solution along the lines of the reflexive survey concept of Kurani et al. appears particularly suitable for the case at hand. Without entirely renouncing the structured data generation process typical of stated choice exercises (which can be designed for reliability of parameter estimates), this approach mitigates the impact of unfamiliarity with the hypothetical context by means of the preliminary reflexive stage.

In the following section the development of the ECarSim tool is presented. This survey instrument, while building on the work of Kurani et al., represents a completely novel application since it is not used to study the demand of electric vehicles as a product, but to analyse choices about their use, with particular emphasis on charging in a smart grid environment. Moreover, ECarSim represents a new methodological development in itself since, in contrast to Kurani et al. (1996)'s multistage approach, it concentrates the reflexive survey process into a single compact stage exploiting the current digital landscape. A single stage survey may have the advantage of mitigating the risk of respondents dropping out between survey phases. Moreover, it has the advantage of allowing an immersive experience and an uninterrupted thought process. Of course, there are limitations to the single stage approach, such as limited time for a thorough maturation of respondents' thoughts regarding the implications of electric vehicle use on travel patterns, although, arguably, even a multiday survey does not guarantee this.

4.3 ECarSim

ECarSim is an internet based interactive data collection tool. It consists of three parts: 1) a questionnaire to extract the socio-demographic characteristics of the respondent and to collect a one-day travel diary; 2) an adaptation of the respondent's travel diary to generate an EV diary, including the specification of the charging timing, in a setting of conventional charging with constant charging power; 3) a stated choice experiment section consisting of two types of tasks, one being a charging settings choice (SCE1), the other being a choice of charging settings and tour timings (SCE2).

4.3.1 Car diaries

In part one, a one-day travel diary is collected for a reference day, i.e. a recent day characterised by frequently undertaken travel episodes.[19] Respondents are instructed to enter

[19] The reference day must contain activity-travel episodes undertaken at a minimum frequency of once a week.

their travel diary as a series of home-based tours. They are given the definition of a home-based tour as an “episode” consisting of: 1. departing from home, 2. travelling to the locations of your activities and performing your activities, 3. returning home. For up to four tours in their reference day they are asked to identify a main purpose and a main destination: “The main purpose of the tour is the main reason that brought you out from home, the main destination is the location where you carried out the activity that is the main purpose”. The timings of the tour are collected with reference to this main purpose/destination. Information on secondary within-tour activities, if existing, is collected only in terms of activity category. In this travel diary data collection phase respondents are made familiar with a graphic summary of the tour characteristics (Figure 11). This graphic summary is then utilised in parts two and three of the survey, so as to remind respondents of the original features of the tour in their car diary.

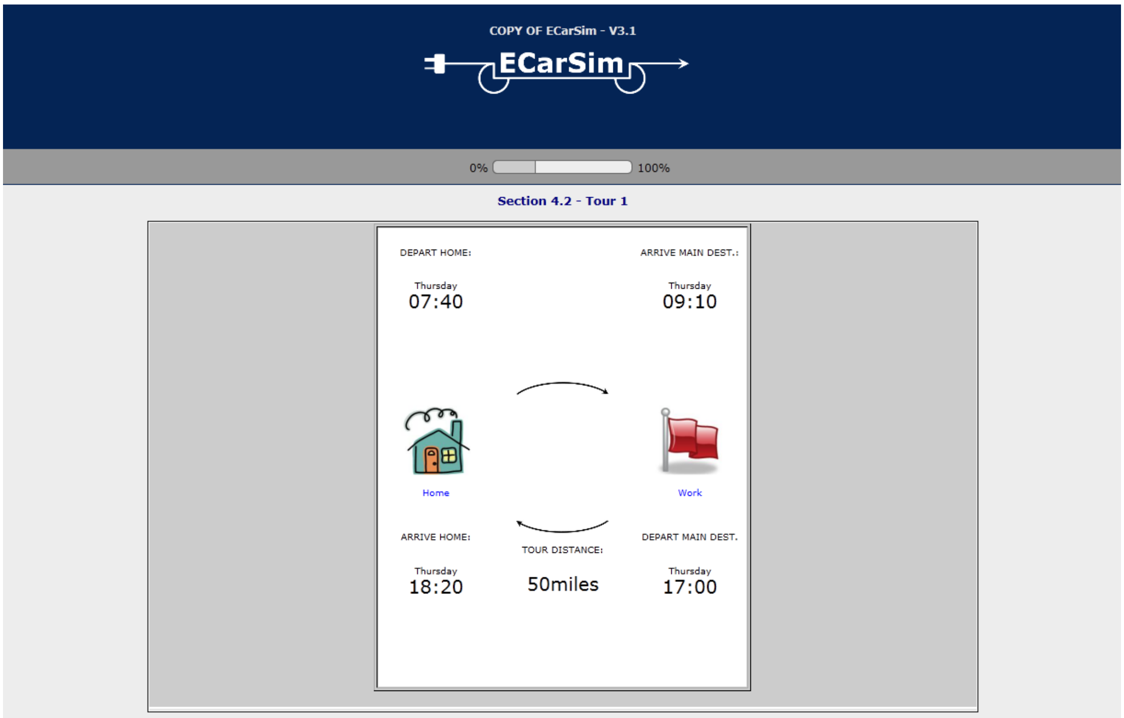

Figure 11 Graphic summary of tour characteristics as presented to respondents in ECarSim

4.3.2 Stated adaptation

In part two of the ECarSim survey respondents engage in a stated adaptation task aimed at making car drivers more familiar with EV use and charging, since this survey is addressed to car drivers, who may not have operated an electric car before.

The stated adaptation task basically consists of making the respondents modify their original car diary so that it is compliant with the driving limits of a specific EV (whose characteristics are summarised in Table 5). This adaptation process involves:

- Setting up home charging operations in such a way as to make the required journeys feasible in an EV context;
- Possibly, amending respondents' original car diaries.

This adaptation process is intended to make respondents familiar with the home charging operation and how it requires a longer time than refuelling, and with the issues that might be involved in getting round with a range-limited vehicle. The practical purpose of this reflexive part of ECarSim is to engage respondents and smoothly introduce them to the hypothetical world, setting the context for the charging choice exercises.

In practice the stated adaptation tasks involves the following steps:

- Respondents are introduced to the characteristics of the EV and made familiar with the terminology involved (see Table 5)
- For each tour in their diary, respondents complete the interactive form shown in Figure 12. This involves recharging their EV at home before departure and possibly modifying:
    - Tour distance (by changing route or main activity location)
    - Tour timings (for instance to allow a longer time at home to achieve a higher battery level before departure).

At the end of this process EV feasible tours are generated.

It should be noted here that in this stated adaptation task the charging speed is fixed and respondents are made aware of this (see Table 5). This means that the battery level can be adjusted only by altering the charging start time and charging end time.

Moreover, the hypothetical context of the stated adaptation task, as well as that of the choice experiments in part three, is built around home charging only.[20] This means that in the stated

[20] Both in the stated adaptation game and the state choice tasks, only home charging is assumed to be available. Respondents are instructed to imagine having the possibility to charge in their garage or driveway, or in case they park on-street near home that on-street chargers are made available to them.

adaptation tasks, a battery level entry is accepted only if it makes feasible the original tour, or an amended version of it.

Finally, note that throughout the stated adaptation task and the following stated choice experiments, wherever information about the battery level is provided, this is done by explicitly stating the following:

- the level expressed as a percentage of the full capacity;
- the level expressed as usable energy units in kWh; and
- the level expressed as a maximum and a minimum nominal range corresponding to consumption levels of 0.4kWh/mile and 0.24kWh/mile[21,22]: this variability in fuel consumption is explained to the respondents as being the effect of the factors listed in Table 5.

Table 5 ECarSim electric car characteristics

Electric car characteristics	**Description to respondents**	**Additional notes provided to respondents, upon request**
Charging speed	"for each hour the vehicle is plugged-in the battery will gain 3 kilowatt-hours (kWh) of energy, corresponding to a driving range of 8 to 13 miles"	- - -
Maximum battery capacity/Range	"24 kWh, corresponding to a driving range of 60 to 100 miles"	"[Range] What is it? • How far you can drive for a given battery level. What are the factors affecting it? • Climate control – heating and air conditioning draw energy from the battery, reducing range; • Speed – higher speed means higher air resistance and thus energy consumption and lower range; • Driving style – smooth driving extends range while aggressive acceleration and deceleration reduces it; • Cargo and topography – increasing cargo weight and driving uphill reduces range."

21 Neglecting rounding errors since, in the choice experiments, energy levels in kWh and range values in miles are expressed as whole numbers.

22 EPA ratings for the Nissan Leaf 2013 are 0.33kWh/mile for highway cycle and 0.26 for city cycles. The higher bound we choose is intended to represent the "nominal" worst driving conditions, while the lowest, which is lower than EPA's rating for the Leaf in city driving, was chosen to represent the highest range nominally achievable for a round number of 100 miles.

This process allows respondents to get familiar with the constraints that using an EV imposes, and also with the idea of charging. While, for simplicity, we call the task in this survey section “stated adaptation”, in fact, it would be more appropriate to refer to it as a “constrained stated adaptation game”. It is “constrained” because in this context the available adaptation options are deliberately limited: timing shifts, activity duration extensions or contractions, location or route modifications. Other possibilities such as activity reshuffling[23] or mode shifts for a complete tour or part of it are excluded. Moreover, while in traditional stated adaptation games, the adaptation of travel is forcibly induced in at least some of the stages of the game, in ECarSim the adaptations may not be required since the electric car characteristics may perfectly fit the original car diary.

[23] Activity reshuffling means changing the order of the activities in one’s diary. This could indeed be a potential adaptation, for instance in the following case. Suppose that one has two tours in one’s diary; an initial feasible tour followed by an unfeasible one, where the unfeasibility may be due to the fact that there is no time to fully recharge. In such a circumstance, scheduling the activities of the first tour to a later day (where feasible), may be an adaptation that enables the feasibility of the second tour.

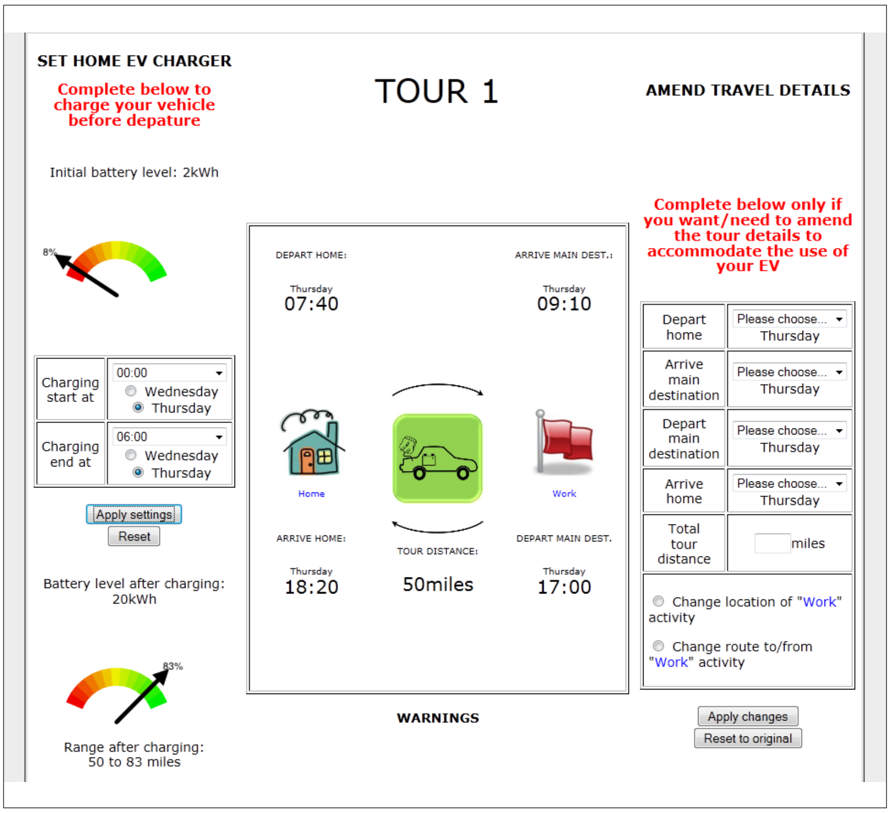

Figure 12: Stated adaptation task

4.4 Stated choice experiments

The third main part of ECarSim contains the stated choice experiments, aimed at eliciting charging behaviour in a hypothetical smart grid context.

This context is introduced by describing the charging operation as being carried out with an advanced charger technology referred to as "smart chargers". Respondents are instructed that smart chargers require as input from them only the "target battery level", i.e. their requested state of charge at the end of the charging operation and the time this is to be achieved, which is referred to in the survey as "time EV ready". Once this information is entered, the smart charger dashboard provides information about the cost of the charging operation. Respondents are also informed that: "The SMART CHARGER will automatically connect to your electricity provider and place your request for charging, that is your TARGET BATTERY LEVEL and your TIME EV READY. The smart charger will manage the charging operation, so that your request is satisfied at the minimum possible cost consuming if possible only "cheap" electricity. To do so the smart charger will autonomously control the rate at which the electricity flows into your battery preventing you from being able to exactly predict the battery level at any given time during the charging operation. However you are guaranteed that TARGET BATTERY LEVEL is reached at the TIME EV READY you chose. Moreover any time before the TIME EV READY you will be able to check the battery level reached so far simply by taking a look at the smart charger's display or via your mobile phone."

After the context is set, respondents face two series of twelve choice situations, respectively choice experiment 1 (SCE1) and choice experiment 2 (SCE2). In all choice situations from both series the respondents are reminded of the features of their first tour of the day using the graphic representation in Figure 11. Then, in the twelve choice situations from SCE1 they are asked to choose amongst two alternative settings for the charging operation occurring during the vehicle dwell time at home before the tour.[24] In SCE1 the duration of the charging operation never exceeds the original observed dwell time at home. The design variables for this series are the battery level after charging, the duration of the charging operation and its cost. In SCE2 the charging duration can exceed the original vehicle dwell time at home, thus potentially delaying the departure. Moreover, for a given charging alternative, respondents can choose to reduce the time spent at the main activity destination to partially absorb the schedule delay. Alternatives to electric car use are also offered.

Both in SCE1 and SCE2, the battery level before charging (i.e. the initial battery level) and the start charging time are fixed across the choice situations. In particular, the charging start time is coincident with the arrival time at home from the last car journey before the reference day, unless this journey terminated before 12am on the day preceding the reference day, in which case, the charging start time was fixed exactly to 12am of the day preceding the reference day. The initial battery level value is discussed in the next section.

4.5 Design of first stated choice experiment

As previously mentioned, the attributes characterising a generic home charging alternative are:

- Battery level after charging
- Charging cost
- Duration of the charging operation, (i.e. the elapsed time from the arrival time at home from a previous car tour and the departure time of the next tour).[25]

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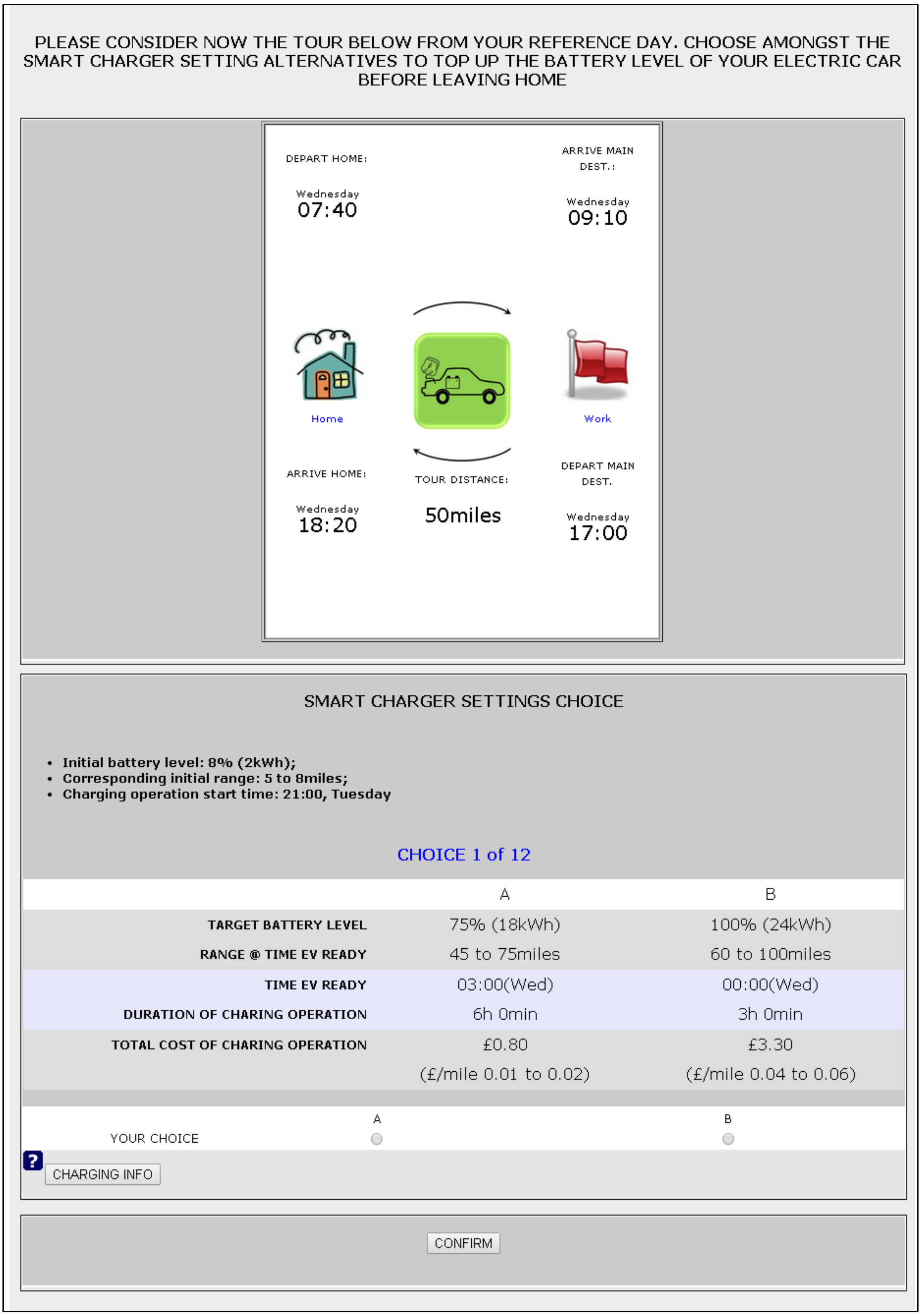
[24] All respondents are told that they can charge only at home. See also footnote 20

[25] Respondents are told to imagine that they plug-in their electric vehicle as they arrived at home.

In each choice task these three attributes are presented in different forms to provide the necessary information in the clearest possible way. The first attribute is presented to the respondent in three ways: in terms of battery state of charge SOC, (“TARGET BATTERY LEVEL”), i.e. as percentage of the full capacity (as in a fuel gauge), in energy units (kWh) available after charging and in terms of range interval, where the low boundary corresponds to a lowest nominal efficiency and the high boundary correspond to the nominal efficiency in ideal driving conditions.The charging cost information is presented in terms of total charging cost and cost per mile interval (low and high boundaries correspond to the high and low nominal efficiencies respectively). The charging duration attribute is presented as time elapsed from arrival until the target battery level is reached (“DURATION OF CHARGING OPERATION”), and in terms of the instant at which the charging operation terminates (“TIME EV READY”).

The battery level before charging is also required information provided to respondents so that they can make their choice. Figure 13 shows how a choice situation for this experiment would appear to a respondent.



PLEASE CONSIDER NOW THE TOUR BELOW FROM YOUR REFERENCE DAY. CHOOSE AMONGST THE SMART CHARGER SETTING ALTERNATIVES TO TOP UP THE BATTERY LEVEL OF YOUR ELECTRIC CAR BEFORE LEAVING HOME

DEPART HOME:
Wednesday
07:40

ARRIVE MAIN DEST.:
Wednesday
09:10

Home

Work

ARRIVE HOME:
Wednesday
18:20

TOUR DISTANCE:
50miles

DEPART MAIN DEST.
Wednesday
17:00

SMART CHARGER SETTINGS CHOICE

- **Initial battery level: 8% (2kWh);**
- **Corresponding initial range: 5 to 8miles;**
- **Charging operation start time: 21:00, Tuesday**

CHOICE 1 of 12

	A	B
TARGET BATTERY LEVEL	75% (18kWh)	100% (24kWh)
RANGE @ TIME EV READY	45 to 75miles	60 to 100miles
TIME EV READY	03:00(Wed)	00:00(Wed)
DURATION OF CHARING OPERATION	6h 0min	3h 0min
TOTAL COST OF CHARING OPERATION	£0.80	£3.30
	(£/mile 0.01 to 0.02)	(£/mile 0.04 to 0.06)

A
B
YOUR CHOICE

?
CHARGING INFO

CONFIRM

Figure 13: Example of choice situation in the first series of discrete choice experiments

4.5.1 Description of attribute levels

INITIAL BATTERY LEVEL

It was decided to choose an initial battery level at the start of the dwell time at home that would make the charging operation unavoidable in order to complete the return journey home for all respondents. Two simple possible solutions are the following:

- Making use of the distance information provided by each respondent in the travel diary section of the survey, and setting a respondent-specific initial battery level that is low enough to make the tour unfeasible without charging at home.
- Fixing a single initial battery level for all respondents; and pre-selecting the respondents (based on tours they carry out regularly) who are likely to face tours that are unfeasible with that initial battery level, but feasible if the EV is charged at home for some non-zero duration.

Because the survey is addressed to general car drivers, and not habitual EV drivers, any *a priori* assumption of what could be a more realistic minimum level at which they would charge an EV would not be really grounded It was therefore decided to fix the same initial battery level for all to the same low value (8% of the full charge, i.e. 2kWh corresponding to a range interval of 5 to 8 miles).[26] Moreover, it was decided, to focus the stated choice task on home charging before long distance tours, in the range of 30 to 80 miles.[27]

TARGET BATTERY LEVEL

The target battery levels in the stated choice tasks must be respondent-specific because they all must guarantee that the (respondent-specific) tour distance is at most equal to the upper bound of the range interval corresponding to each target battery level in the design of the choice experiment. In other words, the target battery levels must imply feasible tours.

In order to capture potential nonlinear effects four levels were selected for the 'Target Battery Level' attribute. Level, k for respondent n is defined, in energy unitis (kWh), as follows:

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[26] This solution also was the most parsimonious of the two in terms of the JavaScript code needing to run in real-time. In general, reducing the amount of the JavaScript code needing to run in real-time reduces the upload time of a webpage of the survey.

[27] Respondents were pre-screened to comply with the requirement of carrying out at least once a week a regular tour of a total return distance between 30 and 80 miles. Section 4.8 details the reason for focusing on this distance range.

$$E_{nk} = E^0 + Q_n^{req} + k\frac{Q_n^{max}}{4}, \quad k = 1,2,3,4 \tag{4.2}$$

where

$$Q_n^{req} = \max\left(E_n^{(req)} - E^{(0)}, 0\right) \tag{4.3}$$

and

$$Q_n^{(max)} = \left(\min\left(r^{(max)}T_n^H, E^{(\mathrm{SOC}_{100\%})} - E^{(0)}\right)\right) - Q_n^{req} \tag{4.4}$$

In the two expressions above $E_n^{(req)} = cd_n$ is the energy that has to be stored into the battery required to complete a tour of distance d_n assuming consumption c. The latter parameter (c) was fixed to 0.24 kWh/mile across respondents and choice situations; this energy consumption value is the nominal minimum, and underlies the upper bound of the nominal EV range interval that in the stated choice tasks is presented as corresponding to a given target battery level value.

In the choice alternatives, the levels of available energy after charging E_{nk} can take for respondent n four values as $k = 1,2,3,4$. These mean that $\mathrm{E_{nk}}$ is always greater than $E_n^{(req)}$. However, E_{nk} is not necessarily greater than the required battery level necessary to complete the tour at the maximum consumption, and this leads to ambiguity in tour feasibility, which will be discussed later in this chapter.

The highest available energy level after charging respondent n ($\mathrm{E_{n4}}$) in the choice experiment is equal to a maximum charging power $\mathrm{r^{(max)}}$ times the vehicle dwell time at home before the tour, as observed in the respondent travel diary $\mathrm{T_n^H}$, plus the energy stored in the battery before charging $\mathrm{E^{(0)}}$. $\mathrm{E_{n4}}$ is, however, capped to the battery capacity $\mathrm{E^{(SOC_{100\%})}}$. This limit is taken into account in the above definition of the term $\mathrm{Q_n^{(max)}}$. Both maximum charging power and vehicle battery capacity are fixed across respondents (and choice situations) to 7.2kW and 24kWh respectively. While the maximum (usable) battery capacity is the same as in the stated adaptation task, the maximum charging power is higher and matches the charging power level that is commonly referred to as the "fast charging" level in the typical classification of electric vehicle charging infrastructure.[28]

Table 6 shows examples of the four target battery levels in the choice tasks for different driving distances of the tour to be undertaken after charging, calculated according to equations 2 to 4, under the assumption that the T_n^H is greater than 3 hours and 3 minutes, (so that level 4, the highest, corresponds to the full battery).

Table 6: Levels of the target battery level attributes based on tours of several distances and dwell times at home before departure above 3 hours. Note that, these levels are those presented to the respondents, and included rounding[29]

Levels	**d_n=30miles**	**d_n=40miles**	**d_n=50miles**	**d_n=60miles**	**d_n=70miles**	**d_n=80miles**
$\boldsymbol{E_{n1}}$	11	14	15	17	19	20
$\boldsymbol{E_{n2}}$	16	17	18	19	21	22
$\boldsymbol{E_{n3}}$	20	21	21	22	22	23
$\boldsymbol{E_{n4}}$	24	24	24	24	24	24

CHARGING DURATION

The charging duration attribute is also assigned four levels (CT_{nk}): obtained as follows

$$CT_{nk} = \frac{\max\left(E_n^{(req)} - E^{(0)}, 0\right)}{r^{(max)}} + \frac{k}{4}\left[T_n^H - \frac{\max\left(E_n^{(req)} - E^{(0)}, 0\right)}{r^{(max)}}\right], \qquad (4.5)$$

$$k = 1,2,3,4$$

The maximum charging duration (k=4) in this choice experiment coincides with the vehicle dwell time at home before the tour as reported by respondents in their travel diary; i.e. in this choice experiment no charging alternative entails a delayed departure with respect to the original departure time from home. Table 7 shows examples of the four charging duration levels, for several $\mathrm{T}_\mathrm{n}^\mathrm{H}$, and the driving distances of the tour to be undertaken after charging.

[28] More precisely, fast charging is the colloquial denomination for a charging mode that allows full charging of a typical 24 kWh battery in 1 to 3 hours. This is typically achieved via Mode 3 charging, with a fixed dedicated circuit (230 Volts, 32A, 63A, 100A) (BEAMA, 2012). For fast home charging 230V, 32A chargers are being commercialised with a 7.2kW rated output (PodPoint, 2012).

[29] These values are obtained after rounding to the kWh $E_n^{(req)}$ before using it in equation (1.3) and finally rounding to the kWh E_{nk}

Table 7: Example of charging duration levels for several combinations of observed vehicle dwell time home before departure, and tour distances

	d_n=30miles	d_n=40miles	d_n=50miles	d_n=60miles	d_n=70miles	d_n=80miles
Levels, T_n^H=8h						
CT_{n1}	02h 30min	02h 50min	03h 00min	03h 20min	03h 30min	03h 50min
CT_{n2}	04h 20min	04h 30min	04h 40min	04h 50min	05h 00min	05h 10min
CT_{n3}	06h 10min	06h 20min	06h 20min	06h 30min	06h 30min	06h 40min
CT_{n4}	08h 00min	08h 00min	08h 00min	08h 00min	08h 00min	08h 00min
Levels, T_n^H=12h						
CT_{n1}	03h 30min	03h 50min	04h 00min	04h 20min	04h 30min	04h 50min
CT_{n2}	06h 20min	06h 30min	06h 40min	06h 50min	07h 00min	07h 10min
CT_{n3}	09h 10min	09h 20min	09h 20min	09h 30min	09h 30min	09h 40min
CT_{n4}	12h 00min	12h 00min	12h 00min	12h 00min	12h 00min	12h 00min
Levels, T_n^H=24h						
CT_{n1}	06h 30min	06h 50min	07h 00min	07h 20min	07h 30min	07h 50min
CT_{n2}	12h 20min	12h 30min	12h 40min	12h 50min	13h 00min	13h 10min
CT_{n3}	18h 10min	18h 20min	18h 20min	18h 30min	18h 30min	18h 40min
CT_{n4}	24h 00min	24h 00min	24h 00min	24h 00min	24h 00min	24h 00min
Levels, T_n^H=36h						
CT_{n1}	09h 30min	09h 50min	10h 00min	10h 20min	10h 30min	10h 50min
CT_{n2}	18h 20min	18h 30min	18h 40min	18h 50min	19h 00min	19h 10min
CT_{n3}	27h 10min	27h 20min	27h 20min	27h 30min	27h 30min	27h 40min
CT_{n4}	36h 00min	36h 00min	36h 00min	36h 00min	36h 00min	36h 00min
Levels, T_n^H=48h						
CT_{n1}	12h 30min	12h 50min	13h 00min	13h 20min	13h 30min	13h 50min
CT_{n2}	24h 20min	24h 30min	24h 40min	24h 50min	25h 00min	25h 10min
CT_{n3}	36h 10min	36h 20min	36h 20min	36h 30min	36h 30min	36h 40min
CT_{n4}	48h 00min	48h 00min	48h 00min	48h 00min	48h 00min	48h 00min

CHARGING COST

The charging cost levels for respondent n are obtained by multiplying the amount of energy charged ($E_{nk} - E^{(0)}$) multiplied by one of three unit price levels: £0.05/kWh, £0.15/kWh and £0.30/kWh. The first price is representative of the off-peak domestic electricity prices in the Economy 7 tariff regime[30], whereas the second is between a regular (non time-of-day) and a representative peak price in Economy 7. The third level is introduced to extend upward the range of domestic electricity prices. Note that in 2012, the average domestic electricity price (including taxes) in the UK was £0.1393/kWh (QEP, 2013). Note also that £0.15/kWh,

[30] Economy 7 UK time of use tariff for domestic energy which has a cheaper price over 7 hours in night time (typically 11pm to 7am)

assuming a consumption of 0.24kWh/mile, corresponds to £0.036/mile, which is approximately 30% of the fuel cost per mile of a petrol Ford Focus.[31]

4.5.2 Statistical design

The experimental design of SC1 is based on an individual respondent level efficient design approach. This approach is similar to the one proposed by Rose et al. (2008) for the design of choice experiments in the presence of a reference alternative.

A design for a choice experiment consists of choice sets composed of a number of alternatives (two in the present case) each of which is a combination of attribute levels. The objective of the experimental design is to obtain a design such that the parameters of the choice model are estimated with high precision. A design with such characteristics is said to be efficient; if a specific design has maximum efficiency it is optimal.

Several measures of the design efficiency exist, but the most widely used in the literature and what we adopt here, is D-error (Rose et al., 2008). The D-error is defined as the geometric mean of the eigenvalues of the asymptotic variance-covariance (AVC) matrix of the design, and is a measure of the size of the error. The goal of efficient design algorithms is to search for designs with an increasingly smaller D-error.

In order to search for increasingly efficient design one has to change the previous design and check whether the newly obtained one is more efficient. There are two families of algorithms that have been proposed to best change the design to locate a more efficient design: row based algorithms and column based algorithms. In the first case, the choice situations are chosen from a pre-defined set of choice situations (e.g. a full factorial or a fractional factorial). In column based algorithms, the design is generated by choosing amongst the possible attribute levels over all choice situations, (Rose et al., 2008).

Although in general, it is easier to include constraints in a row based algorithm, (as is the case for SCE1), a column based algorithm was chosen here because there is a readily available column based procedure from which to draw from and this made it easier to implement.

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[31] The fuel cost for a Ford Focus 1.6 Duratec Ti-VCT (85PS) 5 Door, is rated as £ 1,572 for 12,000 miles, (VCA, 2013). This gives a cost per mile of 13.1p/mile.

The most applied column based algorithms are the RSC (Relabeling, Swapping and Cycling) algorithms (Huber and Zwerina, 1996, Sándor and Wedel, 2001). Relabeling means switching all the levels of an attribute in a column (i.e. across all choice situations); swapping means switching the levels of an attribute at a time; cycling means replacing all levels of an attribute for all choice situations so that level 1 becomes level 2, level 2 becomes level 3 and so on (the last level becoming level 1).

Moreover, constraints to the combination of attribute levels have been introduced in the design search procedure as follows:

- Maximum charging power constraint - his constraint was introduced into the design procedure in order to ensure that combinations of different attribute levels comply with a maximum charging power compliant with a realistic fast charging operation at home (7.2 kW).
- Minimisation of dominant alternatives – Constraints were also introduced in the design procedure to minimise the presence of a dominant alternative. Under the assumption that shorter charging durations are preferred to longer ones, higher available energy levels (i.e. battery levels) are preferred to lower ones, and lower costs are preferred to higher: choice situations such as the following were excluded:
    - Available energy alternative A > Available energy alternative B
    - Charging duration alternative A < Charging duration alternative B
    - Unit price alternative A < Unit price alternative B.

The AVC matrix and its determinant are calculated under the assumption that the underlying choice model is a multinomial logit model. The calculation of the AVC does not require the choice outcomes, which of course are not available at the stage of the experimental design, but requires priors for the model parameters. Estimates of the priors used in the efficient design procedure were obtained from the pilot of the survey administered to PhD students and staff of the Department of Civil and Environmental Engineering at Imperial College London (see section 4.7).

Previously in this section we have shown how the attribute levels are individual specific and how their definition requires information from earlier parts of the survey. This means that, in order to keep the survey to one stage (i.e. to avoid dividing it into parts that require re-contacting respondents), the individual respondent level efficient design algorithm needed to be run online. A client based solution was chosen for this purpose and the algorithm was coded in JavaScript. To keep the run time of the script low it was decided to limit the number of algorithm iterations. The number of swaps was fixed so that the stated choice task page of the online survey would not take more than 2-3 minutes to load.

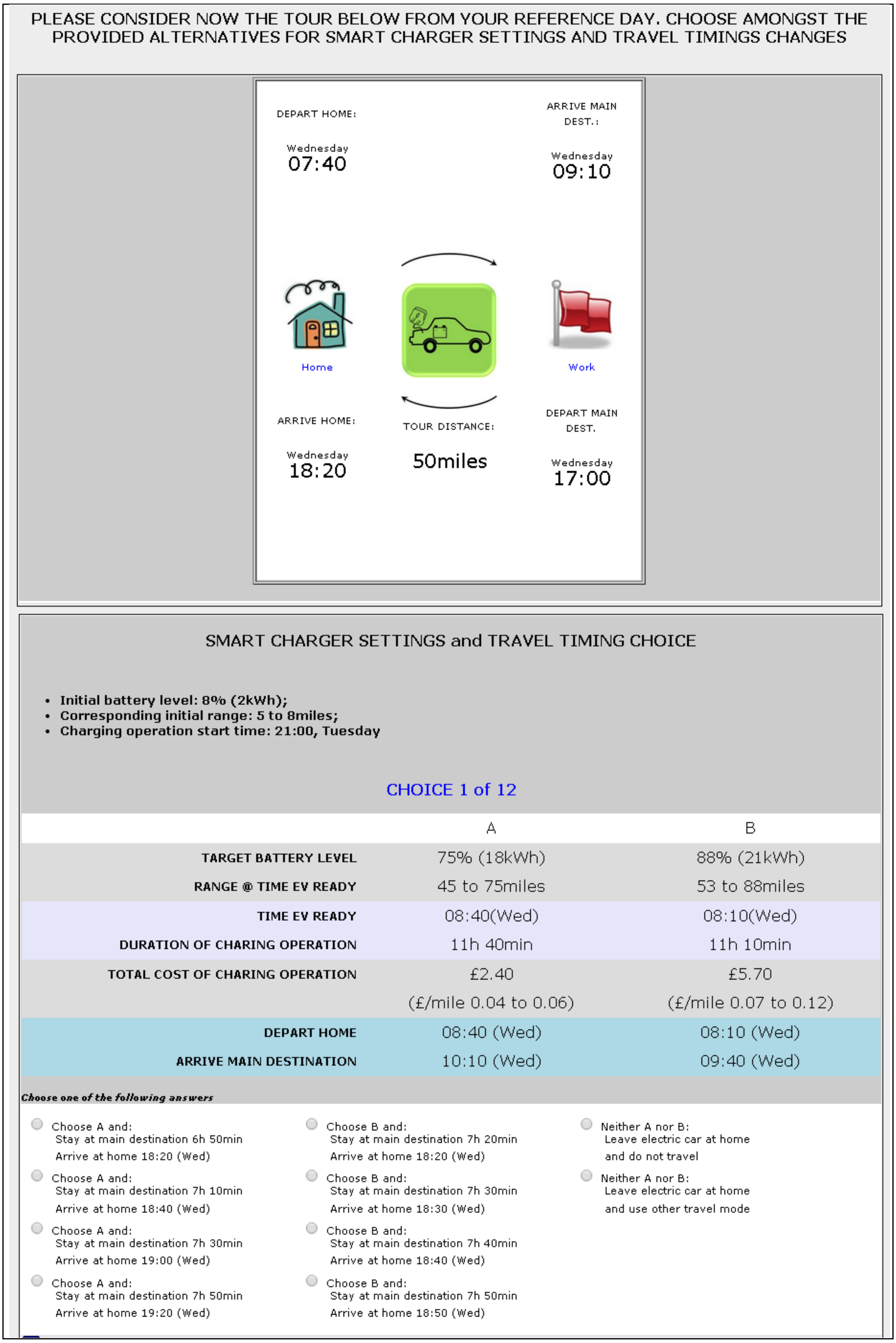
Table 8 Summary of the SCE1 design search procedure

Efficiency measure	Algorithm for efficient design search	Specific characteristics
D-error	Column based RSC (Relabeling, Swapping and Cycling) type algorithm (*)	Individual respondent level design: the design is generated by "optimising the efficiency of the design at the individual respondent level, using only a small number of different design iterations per individual" (Rose et al., 2008)

(*) Only the swapping procedure is implemented, to limit the duration of the online JavaScript run. As a matter of fact the simultaneous use of all the three procedures: relabeling, cycling and swapping is not required (Rose et al., 2008).

4.6 Design of second stated choice experiment

In the second series of choice situations the charging operation duration is either equal to or exceeds the original vehicle dwell time at home, thus introducing a potential schedule delay with respect to the original departure time. The number of design variables remains the same as in the first choice experiment, but the schedule delay replaces the duration of the charging operation as a design variable. Moreover, instead of simple binary choices, respondents have the option to choose, for a given charging setting alternative, how to distribute the delay between activity contraction at the main destination and schedule shift. Furthermore, alternatives to electric car use are offered, such as "change mode" or "do not travel". The maximum number of activity contraction levels is four, including no activity contraction. The number of activity contraction levels for a given schedule delay is chosen so that differences in activity participation time at the main destination are at least 10 minutes. An example of a choice task for this second stated choice is shown in Figure 14. In the figure presented, alternative A requires a charging operation terminating one hour later than the departure time in the original tour (at 8:40 am, instead of 7:40 am), implying a schedule delay late. Given charging alternative A, a respondent can decide to absorb part of the hour long delay by spending a shorter time at the destination (either of 20, 40 or 60 minutes) or to simply spend the same time as in the original tour (7.50 hours) and thus arrive home one hour later. Alternative B is analogous only the schedule delay is 30 minutes and the options to curtail the time spent at the destination are 10, 20 or 30 minutes. If both charging alternatives are unacceptable to the respondent, then he/she can choose to avoid them (either by staying at home or by changing travel mode).



PLEASE CONSIDER NOW THE TOUR BELOW FROM YOUR REFERENCE DAY. CHOOSE AMONGST THE PROVIDED ALTERNATIVES FOR SMART CHARGER SETTINGS AND TRAVEL TIMINGS CHANGES

DEPART HOME:
Wednesday
07:40

ARRIVE MAIN DEST.:
Wednesday
09:10

Home

Work

ARRIVE HOME:
Wednesday
18:20

TOUR DISTANCE:
50miles

DEPART MAIN DEST.
Wednesday
17:00

SMART CHARGER SETTINGS and TRAVEL TIMING CHOICE

- **Initial battery level: 8% (2kWh);**
- **Corresponding initial range: 5 to 8miles;**
- **Charging operation start time: 21:00, Tuesday**

CHOICE 1 of 12

	A	B
TARGET BATTERY LEVEL	75% (18kWh)	88% (21kWh)
RANGE @ TIME EV READY	45 to 75miles	53 to 88miles
TIME EV READY	08:40(Wed)	08:10(Wed)
DURATION OF CHARING OPERATION	11h 40min	11h 10min
TOTAL COST OF CHARING OPERATION	£2.40	£5.70
	(£/mile 0.04 to 0.06)	(£/mile 0.07 to 0.12)
DEPART HOME	08:40 (Wed)	08:10 (Wed)
ARRIVE MAIN DESTINATION	10:10 (Wed)	09:40 (Wed)

Choose one of the following answers

- Choose A and: Stay at main destination 6h 50min; Arrive at home 18:20 (Wed)
- Choose A and: Stay at main destination 7h 10min; Arrive at home 18:40 (Wed)
- Choose A and: Stay at main destination 7h 30min; Arrive at home 19:00 (Wed)
- Choose A and: Stay at main destination 7h 50min; Arrive at home 19:20 (Wed)
- Choose B and: Stay at main destination 7h 20min; Arrive at home 18:20 (Wed)
- Choose B and: Stay at main destination 7h 30min; Arrive at home 18:30 (Wed)
- Choose B and: Stay at main destination 7h 40min; Arrive at home 18:40 (Wed)
- Choose B and: Stay at main destination 7h 50min; Arrive at home 18:50 (Wed)
- Neither A nor B: Leave electric car at home and do not travel
- Neither A nor B: Leave electric car at home and use other travel mode

Figure 14: Example of choice situation in the second series of discrete choice experiments

In this second series of choice experiments (SC2), cost levels are defined as in the previous series. The four levels for the schedule delay are 0, 30 minutes, 1 hour and 2 hours. The levels for the target battery levels are defined as in equation 1.2. The same constraints as in the previous series apply here.

The experimental design also follows the same procedure as in SC1, using target battery level, schedule delay and charging cost as design variables. It was based only on the two charging alternatives A and B. The two additional alternatives *Neither A nor B & No travel* and *Neither A nor B & Use other travel mode*, were added to all choice situations in the second experiment, to provide further options to respondents who may find delayed departures as totally unrealistic for them. Also the activity duration contraction variable was not explicitly included in the statistical design. The options allowing a partial absorption of the schedule delay by contracting the participation time at the destination were included to obtain some information regarding how respondents may adapt to the induced delay.

4.7 Survey pilot

Prior to the full scale data collection the survey instrument was tested amongst staff and students of the Department of Civil and Environmental Engineering (DECEE) as a computer aided personal interview (CAPI). This pilot test was carried out amongst 8 DECEE drivers (96 observation for each choice experiment). The stated choice experiments in the pilot were designed using a fractional factorial orthogonal design for both SCE1 and SCE2. However, while for SCE1 exactly the same design variables as in the full scale deployment version were used, in SCE2 an additional design variable (activity contraction at the main destination) was present, which was dropped instead in the full deployment version. Moreover in the pilot design of SCE2 no alternative to EV use were present. These changes to the SCE2 design are discussed later in this section.

The pilot revealed two general issues: task complexity and difficulties in digesting the information and terminology provided. The first issue particularly affected the stated adaptation task, for which some pilot respondents required more evident instructions on how to properly complete the form. This issue was addressed by emphasising the instructions using bright colours and larger fonts. In order not to compromise reliability due to poor understanding of the terminology, however, it was decided to avoid a self-administered internet based survey for the full-scale data collection, and instead keep it as a CAPI, administered in the presence of a trained interviewer. The trained interviewers could assist respondents to clarify the terminology if this was unclear to them despite the information provided. The increased prospect of reliability represents a trade-off against the reduced sample size that is achievable with this form of deployment. The total number of interviews, given the available resources, was kept to a maximum of 100 respondents.

Most of the changes in the survey instrument from pilot to full deployment were concentrated in the way some questions were posed and information presented. For example, in the travel diary data collection, information about main destination initially asked in terms of postcode often required respondents to search for the location's postcode; this was modified to a task of pinning the destination onto an embedded Google Map.

Two important changes from the pilot to the deployment version were applied to the second series of choice tasks. First, while the pilot version did not have alternatives to electric vehicle charging and use, in the final version as described in Section 4.6, the alternatives of 'not to charge and avoid travelling' or 'change travel mode' were added. This was done because in the pilot it was found that the highest schedule delay was viewed, in some cases, as an unrealistic option. Second, in the pilot, the activity contraction at the main destination was used as a design variable, and appeared as an alternative attribute, however the resulting alternatives presented in terms of reduced activity duration at the main destination were found in some cases to force a behaviour that would not be considered in reality. For this reason, in the deployment version, the curtailment of activity at the destination in order to absorb part of the schedule delay was given as optional and in several alternative levels. This design choice meant renouncing the potential to estimate a reliable activity contraction parameter. This drawback was considered acceptable given that the main objective of the choice experiment was to assess trade-offs between the costs of achieving the target battery level and schedule delays.

Additionally, further questions about demographics were added to the full deployment version of the survey.

After the revisions of the survey were carried out as a result of the pilot amongst DCEE staff and students, a further test was carried out amongst 15 drivers that were recruited outside the college (180 observations for each choice experiment). Drivers from this second test were in fact the first batch recruited as part of the full scale survey administration described in section 4.8. After the responses from these first 15 drivers were reviewed the full scale data collection continued.

In this second test the stated choice experiment design procedure detailed in subsection 4.5.2 was deployed to generate the designs for SCE1 and SCE2. Recall that such procedure requires priors for the parameters in order to calculate the AVC matrix for the efficient design search: multinomial logit (MNL) parameter estimates obtained using data from pilot experiments amongst DCEE staff and students were used.

Choice experiment data from the aforementioned group of 15 drivers were used to estimate MNL models, to see whether the new experiment design procedure would allow obtaining estimate statistically significant estimates of the utility coefficients for available energy, charging duration, charging induce schedule delay, activity participation penalty and charging cost. Indeed, results from this initial small sample seemed promising. The estimated parameters were all significant except those for activity participation penalty, which was expected as in the new design; activity participation penalty was no longer a design variable. Although the, parameter estimates sign reflected the signs of the priors, their magnitude resulted varied, these could not be only a scale effect, because also the trade-off ratios had different magnitude. Never the less as the two test samples were small it was deemed that this variation was acceptable, to continue the investigation with the full scale survey deployment.

4.8 Sampling and survey administration

The decision to administer the survey as a CAPI carried out with the assistance of trained interviewers meant that the available resources could only allow a sample of around 100 respondents.

The field work was outsourced to SRA Ltd,[32] a firm with expertise in conducting transport surveys. The firm's interviewers were personally trained by the author, who also took part in a number of interviews as an observer to ensure that the interview procedure was being followed correctly.

The ideal target population was that of general car owning drivers in the UK. This ownership requirement was introduced to ensure that drivers would pay for their own fuel bill, as EV charging cost is one of the attributes of the ECarSim choice experiments. To this target population, the sampling frame added a driving distance constraint: drivers should make a home-based car tour between 30 to 80 miles at least once a week. The reference day for ECarSim would be the most recent day containing such a tour, around which the hypothetical situations of the choice exercises are designed.

[32] 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/ .

The decision to select the sample using a driving distance interval of 30 to 80 miles was motivated by the necessity to make the choice situation particularly meaningful to the respondents given the considerable fraction of battery capacity required for driving such distances. Using a shorter distance level would potentially induce respondents to pay less attention to the available energy attribute in comparison, for instance, to the cost attribute only. While this, on one hand, may increase the risk of an upwards bias in the marginal utility of the target battery level it, on the other hand, reduces the risk of purely cost driven choices. In fact there is also evidence from electric vehicles trials that some drivers find it difficult to make range predictions (Franke and Krems, 2013a). Thus they might be affected by range anxiety even at lower distance levels, in which case for them the choice situation would be meaningful even if they had to travel shorter distances. However, because respondents in this survey was intended to drivers who do not necessarily have EV experience, selecting long distance tours was considered a straight forward approach to simulate a situation where to charging decision would be a critical one. A further implication of the choice of a driving distance interval of 30 to 80 miles is discussed separately in subsection 4.8.1.

It is recognised that with the available resources it would not have been possible to obtain a representative sample of UK drivers at large, however representative variability in driver demographics was sought by designing target quotas for respondents' demographics. The respondents were recruited to hit a target of at least two or more respondents in the 32 categories generated by a full factorial design of the following two-level variables.

- Gender;
- Age: 17-35 / 36+;
- Employment status: employed / not employed;
- Household income: £10,000 – £29,999 / £30,000+
- Household size: 1-2 / 3+.

The above sampling frame could not be met in practice. In fact, the available time and budget meant that SRA Ltd were forced principally to adopt a pragmatic recruitment method, based on interviewers' contacts although, at least on one occasion, recruitment occurred during a public event in London. The characteristics of the final sample are detailed in section 4.9.

4.8.1 A note on driving distances and ambiguity in tour feasibility

In this subsection we highlight a peculiar feature of SCE1 and SCE2 and its relationship with the driving distances chosen in the sampling frame. The way the target battery level was presented in terms of corresponding range interval embeds ambiguity. This ambiguity depends on the fact that range information is provided as an interval between a minimum and a maximum nominal value. While this ambiguity is present in each alternative, it becomes particularly interesting only when it is put in relation to the driving distance expected in the tour after the charging choice. Consider the two following situations:

a) The driving distance is below (or equal to) the lower bound of the range interval; then the outcomes of the ambiguous prospect are only minimally relevant. A driver may have a larger or a smaller safety buffer,[33] but, regardless of the outcome, will be able to complete the tour.

b) The distance falls between the lower and the upper bound of the range interval; then, some outcomes of the ambiguous prospect will be considerably different from others. Some outcomes will be range buffers and some outcomes will be range deficits.[34] Range deficit outcomes entail the inability to complete the tour.

In fact, ignoring safety buffers and range deficits, we could simplify and highlight only two outcomes: tour completion and inability to complete the tour. Therefore, considering only these two outcomes (tour completion and inability to complete the tour), the following holds: charging choice alternatives with battery levels such that situation a) applies, are characterised by a certain outcome, i.e. unambiguous tour feasibility; charging choice alternatives with battery levels such that situation b) applies, are ambiguous prospects, i.e. the tour feasibility after charging is ambiguous.

A practical example may further clarify the meaning of ambiguous feasibility. Suppose that the target battery level is 60%. In ECarSim's choice experiments this corresponds to a range interval of 36 to 60 miles. In this situation, a tour of 40 miles is ambiguously feasible in that the range could be higher or lower than 40 miles depending e.g. on how the car is driven, on whether or not the heating or air-conditioning is used, and on the route topology, urban vs. extra-urban driving, etc. These factors may be perceived as out of the direct control of a driver at the time of the charging choice. It is in fact likely that a driver does not have a clear

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[33] The safety buffer can be defined as $SB = \max(R - d, 0)$, where R is the actual range a driver will achieve for a given battery level when undertaking the tour, i.e. the ratio between the available energy at departure and the average consumption during the tour. The safety buffer represents how far the driver could have driven at the same average consumption.

[34] We define the range deficit as $RD = \max(d - R, 0)$. This represents the range that the driver would still need, having exhausted the battery, to complete the tour at the same average consumption from the beginning of the tour till the battery depleted completely.

idea of the likelihood he will drive in certain conditions or others during the tour. This is what may make the charging choice situation ambiguous.

Selecting tour distances between 30 and 80 miles for the stated choice tasks allows variability in the sample between individuals facing choice situations in which both certain and ambiguous prospects occur and individuals for which only ambiguous prospects occurs. The latter are those whose tour driving distance is above 60 miles. In fact, the maximum battery level, 24 kWh, corresponds to a nominal range interval between 60 and 100 miles. Any respondent facing charging choice situations before a tour with a length of more than 60 miles, therefore, will only choose amongst ambiguous alternatives, because all battery levels in their choice sets will have a low range bound lower than their driving distance. As the driving distance decreases, given the four target battery levels defined (equation (4.2)), the number of battery levels (amongst those four) entailing certainty in tour feasibility will increase. Thus the number of alternatives with a certain outcome will increase.[35]

It is acknowledged that sampling tour distances only within a 30 to 80 miles interval, unavoidably leads to the exclusion of a large majority of home-base tour distances driven in the United Kingdom (see Figure 18), which are typically shorter than 30 miles. It can be argued, however, that charging choice situations before tours of a shorter distance (< 30 miles) would not be dissimilar to those before tours belonging to the lower end of the sampled distance interval, at least in terms of the content of ambiguous feasibility charging alternatives.

Ambiguous tour feasibility could indeed affect the respondents' choice behaviour. Long distance drivers, facing more ambiguous choice situations may have a higher sensitivity to target battery level attributes than short distance drivers.

This section concludes with two caveats. Firstly, using the lower bound of the nominal range interval (in relation to the driving distance) to discriminate between ambiguous and certain tour feasibility depends on the assumption that respondents trust the range information provided. It may be possible that risk (or better ambiguity) averse respondents apply safety

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[35] The number of alternatives with a certain outcome would theoretically depend also on the dwell time at home before the tour as observed in the respondent travel diary T_n^H. Indeed, the largest target battery level depends on T_n^H(see equation,1.4). In the sample collected, however, the minimum dwell time at home was above 4 hours. Given the maximum charging power of 7.2 kW, the maximum target battery level in the sample is always 24 kWh.

factors to the range values that are provided, meaning that the actual discriminating range value may indeed be latent. Secondly, some respondents may be so confident in their ability to control the factors that determine range fluctuations that they may not consider any of the alternatives as ambiguous.

4.9 Characteristics of the *ECarSim* sample

The final number of completed reponses was 88. A direct comparison with the ideal sampling frame is not possible because 15% of the respondents in the cleaned sample did not agree to provide information regarding their household income. Nonetheless, the graphs in Figure 15 provide a comparison of the marginal distributions of the sample demographics with those of the general population of UK car owning drivers. Statistics on the population of car owning drivers were obtained from the 2010 National Travel Survey (NTS) dataset. Car owning drivers are identified as main drivers or non-main drivers of household cars. The marginal distributions from the NTS are obtained by weighting the data as prescribed by the DfT (DfT, 2010).

As regards the demographics, the ECarSim sample demographic is distinctive from the population of UK car owning drivers in the following respects:

- Age: the group below 40 years is overrepresented, accounting for 66% of the sample (the reference population figure is 34%);
- Employment status: people with employment are overrepresented, accounting for the 89% of the sample (the reference figure is 70%).

Unfortunately missing income and different income category definitions do not allow an assessment of the income distribution. If the missing income data belonged to the two lower classes, however, the balance between the highest income group and the rest in the ECarSim sample would nearly reflect the reference distribution.

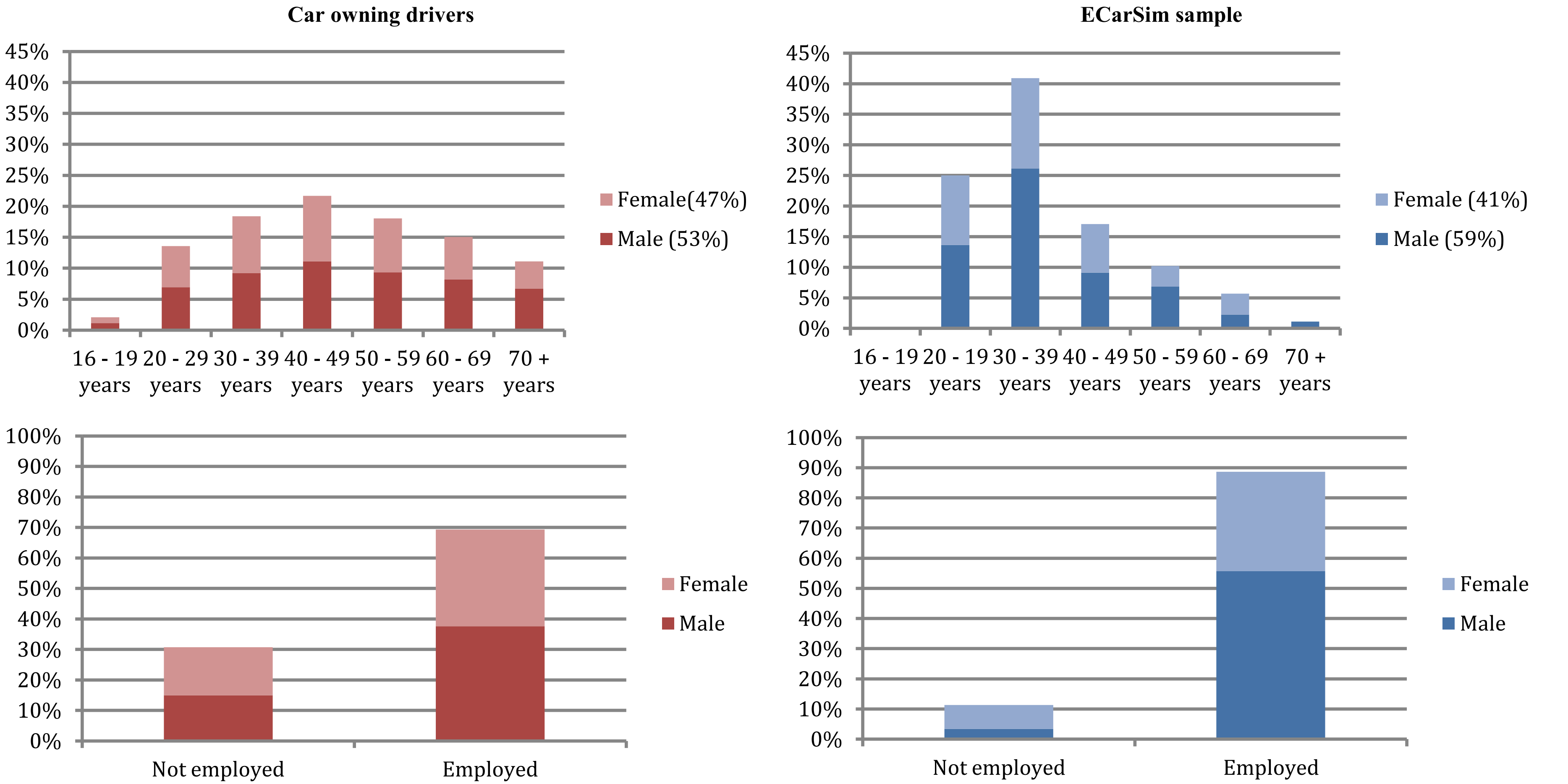


Figure 15 ECarSim sample demographics as compared to UK car owning drivers at large

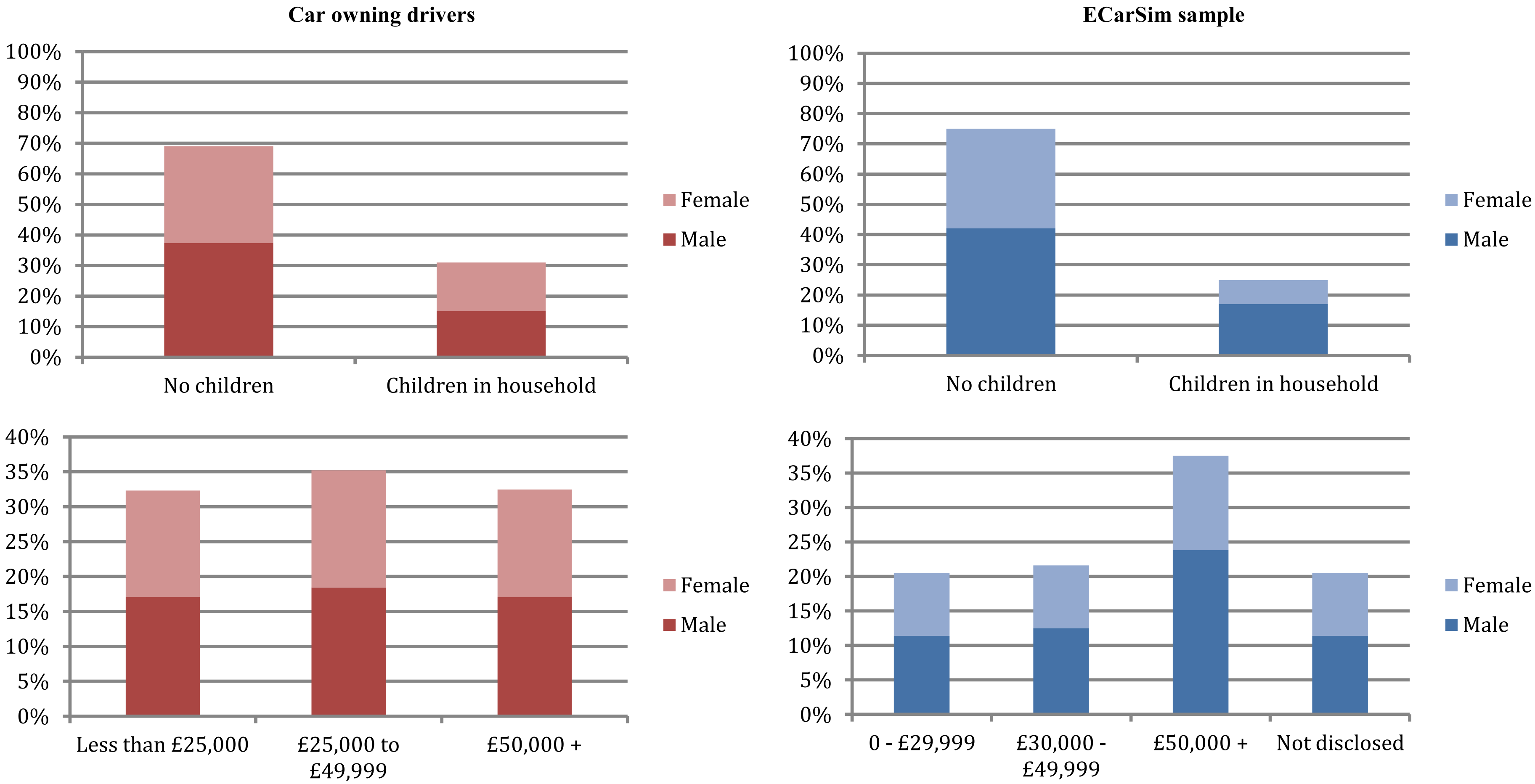


Figure 15 – Continued - ECarSim sample demographics as compared to UK car owning drivers at large

Figure 16 shows that the majority of car owning drivers in the ECarSim sample are resident within the Greater London area. Greater London residents are roughly evenly distributed between central and non-central London boroughs. The sample, therefore, also includes considerable spatial variability with respect to the respondents' home locations. Moreover, Figure 17 shows the characteristics of the tours extracted from the respondents' diaries, which are used to set the choice scenarios in the two series of discrete choice experiments. Recall that the sample was recruited in order to obtain tour distances varying between 30 and 80 miles: 54% of the overall tour distances are within 40 miles. The vehicle dwell times vary considerably and a substantial share (36%) is as long as or longer than 24 hours. Note that the tour distance interval represented in the ECarSim sample reflects only 13% of the tours undertaken by household owned cars in the NTS 2010 sample, and this share is even lower for cars of households living in London boroughs (Figure 18). In other words, the ECarSim sample is disproportionately biased towards longer tour lengths. As previously discussed, however, the choice of this tour distance interval was decided for the practical reason of making the charging choice situations meaningful for the respondents.

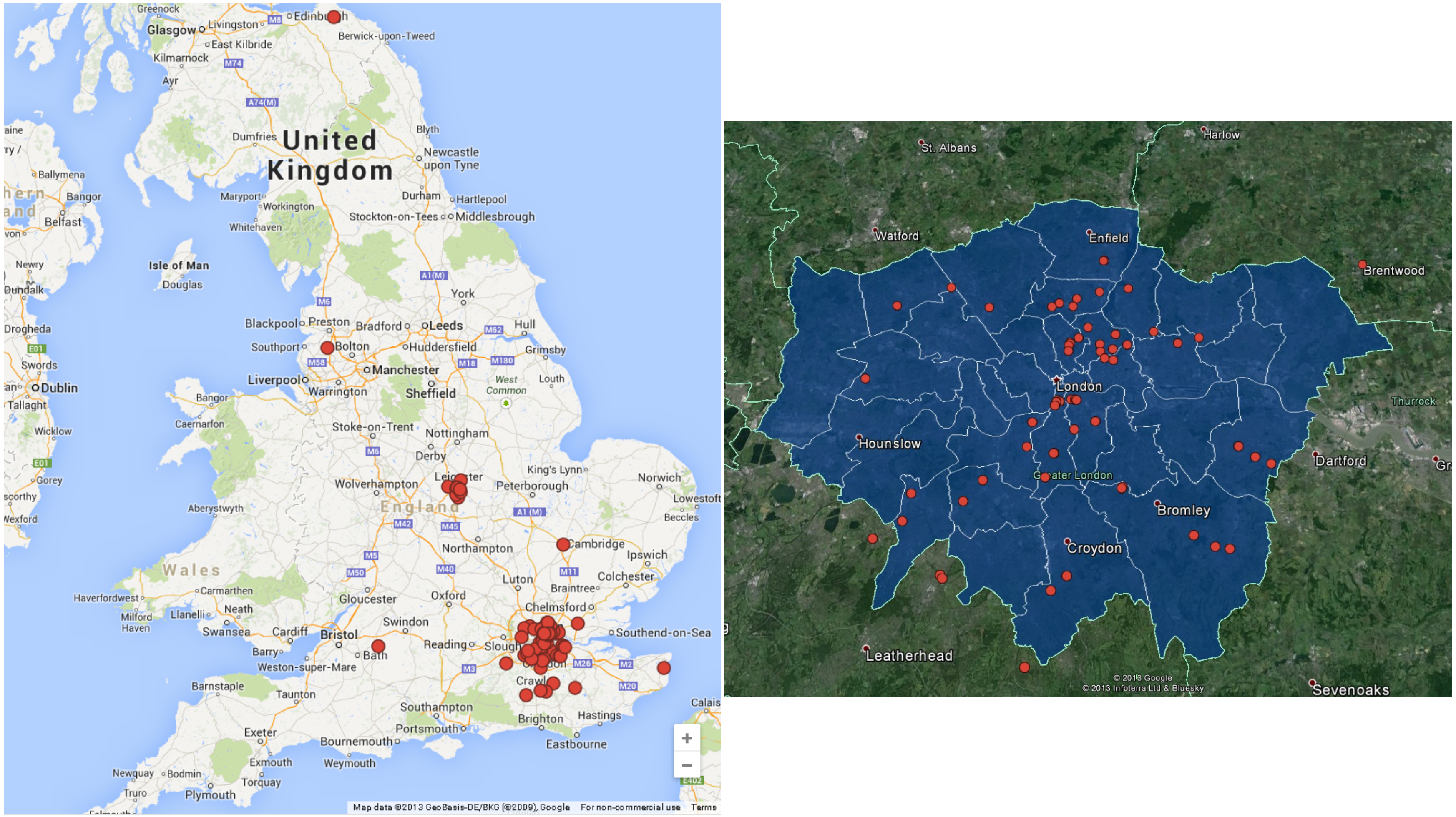


Figure 16 Home locations of drivers in the ECarSim sample, throughout the UK and within the Greater London Area

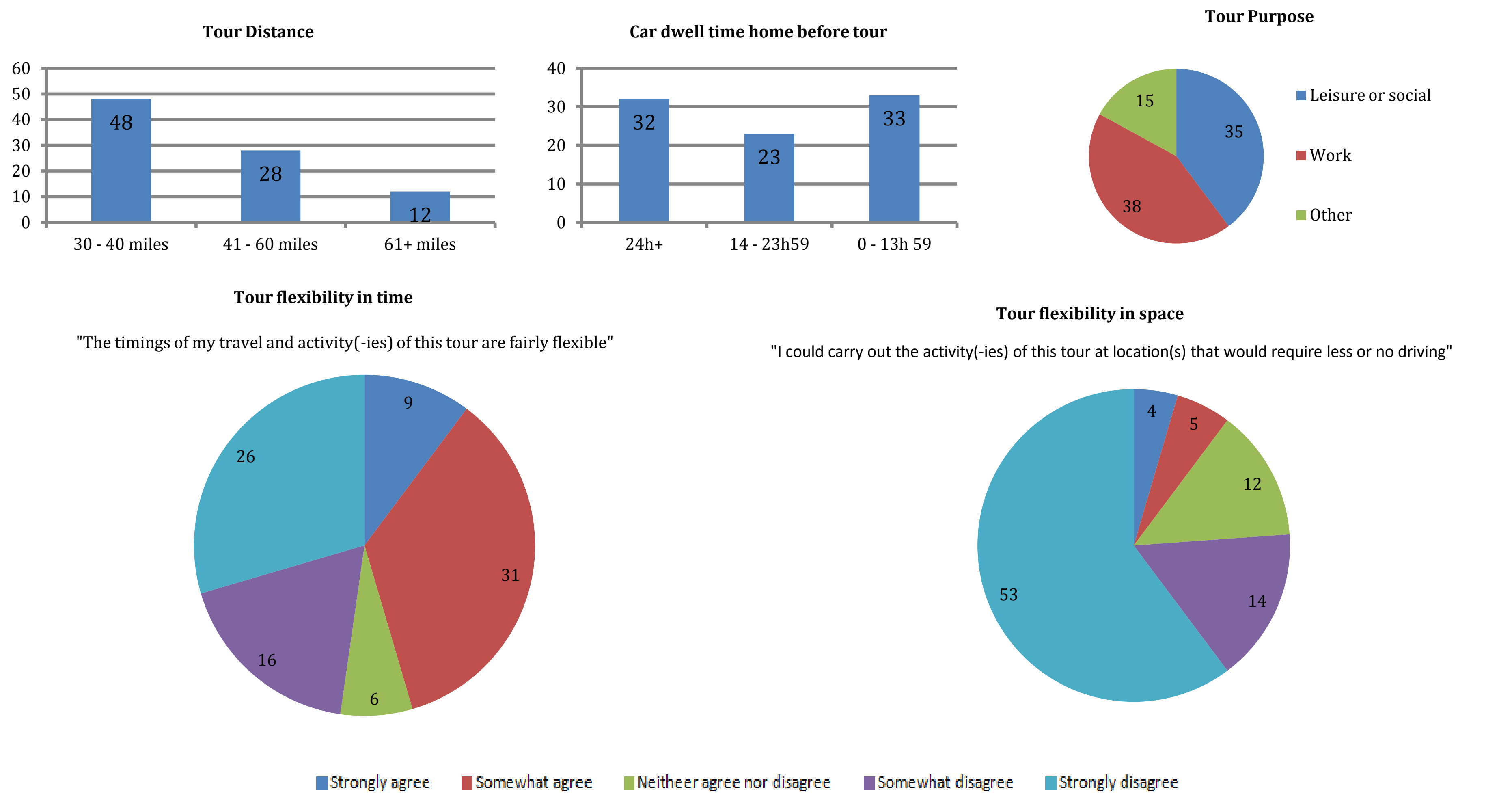
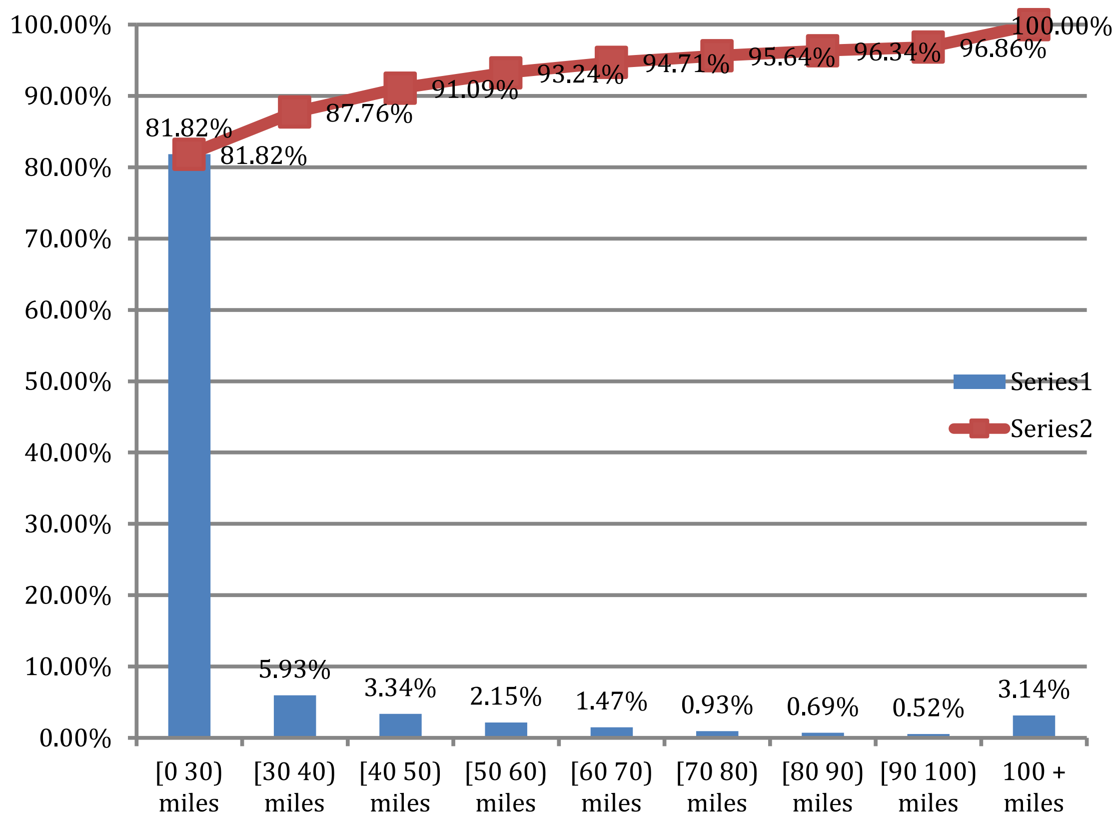


Figure 17 Characteristics of the car tours in the ECarSim sample, used for the stated choice tasks (top graphs); flexibility in time and space of these tours as stated by respondents (bottom graphs).



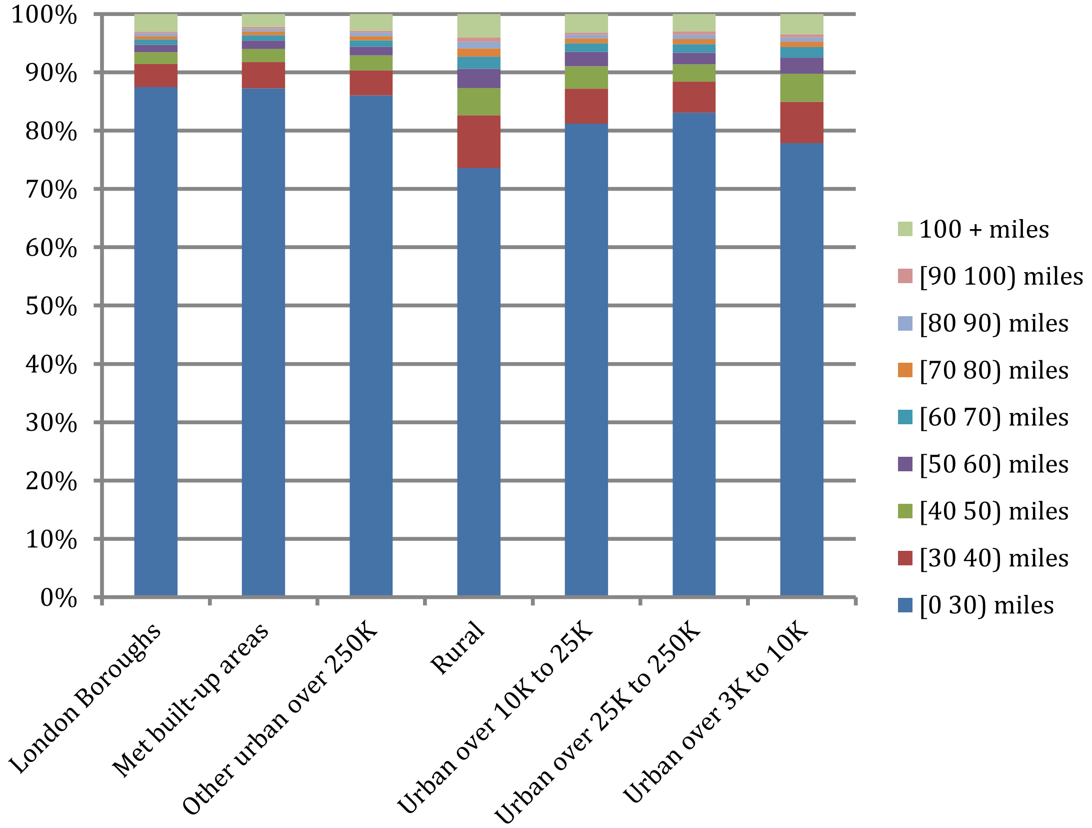


Figure 18 Distribution of car tour distances from the UK National Travel Survey (NTS) 2010: total (top) and by area type. No weights have been applied.

Chapter 5 CHARGING BEHAVIOUR ANALYSES

5.1 Overview

Chapter 3 described the development of a modelling framework to study electric vehicle use scheduling and charging (EVUSC) decisions. This framework is intended to enable the assessment of the potential impact of charging demand response measures.

The modelling framework captures trade-offs between the available energy stored in the battery, charging duration and charging costs, as a function of the tariff structures put in place by charging service providers or electricity suppliers. Moreover, the model highlights how the charging choice becomes entangled with travel timing choices when a charging option entails a late departure in order to allow the completion of the charging operation to the desired battery level.

A tour-based version of the modelling framework, amenable to empirical analysis was also presented in Chapter 3. Chapter 4 detailed the survey, ECarSim, which was developed to collect data in the form of choice experiments to estimate the salient parameters of this empirical model, in particular: the marginal utilities for available energy; charging duration and (charging induced) schedule delay, as well as a cost coefficient.

The primary aim of this chapter is to investigate EVUSC decisions making use of the choice experiment data available from the ECarSim survey and to obtain estimates of those parameters of the model set out in Chapter 3 which are attainable using stated choice experiment 1 (SCE1) and stated choice experiment 2 (SCE2).

The specific objectives of this chapter, therefore, are:

- To use data from SCE1 and SCE2 to obtain estimates of the above parameters.
- To gain insights into charging behaviour by:
    - Analysing observed and unobserved heterogeneity in tastes for charging attributes and offering interpretations for these.
    - Introducing a modelling framework to formally accommodate the effect of range anxiety on charging choices, and providing empirical results, showing their effect on taste for available energy.

The structure of the present chapter is as follows:

- Section 5.2 presents the discrete choice modelling procedures used in this chapter to analyse the results from the choice experiments.
- Section 5.3 presents analyses of SCE1, more specifically it provides
    - the review of the purpose of SCE1 and a presentation of general hypotheses for the model parameters;
    - the estimation of a base multinomial logit model (MNL) specification;
    - diagnostic analyses to investigate results for the base specification that were found partially contradicting the general hypotheses for some model parameters.
    - the estimation of a MNL final specification accounting for systematic heterogeneity in the charging attributes;
    - the estimation of a mixed logit specification to gauge the residual heterogeneity in the charging attributes when sources of systematic heterogeneity are accounted for;
- Section 5.4 analyses the effects of range anxiety on a subset of observations from SCE1 using an integrated choice latent variable approach.
- Section 5.5 presents analyses of SCE2: a base MNL specification and specifications accounting for systematic and unobserved taste variation are estimated.
- Section 5.5 gives a summary highlighting the original contributions provided by the research reported.

5.2 Methods of analysis

SCE1 and SCE2 provide stated preference information about respondents' charging choices. Discrete choice experiments such as these are typically analysed using discrete choice models (Louviere et al., 2000, Ortuzar and Willumsen, 2011, Train, 2009). A brief introduction to discrete choice models was presented in Chapter 3, when electric vehicle adoption models were reviewed. For a detailed presentation of discrete choice theory the interested reader is referred to textbooks by Ben-Akiva and Lerman (1985b) and Train (2009). In this section only the models utilised in this chapter are discussed

The multinomial logit model (MNL) is used to estimate the charging choice parameters from both SCE1 and SCE2 and to explore systematic taste heterogeneity. Moreover the random coefficient mixed logit model is estimated to quantify the residual unobserved variability in taste for available energy, charging duration and schedule delay.

In addition, an integrated choice and latent variable (ICLV) model is estimated in this chapter on a subset of observations from SCE1 in order to model the effect on charging choice of the latent construct 'range anxiety'.

5.2.1 Notation in discrete choice models

The most common theoretical framework underlying discrete choice modes is random utility theory. This assumes that:

- Individual n always selects the alternative that maximises theory utility.
- These is a set of available alternatives J_{ns} from which individual l chooses in a given choice situation (s);
- Each alternative j is associated to a utility U_{nsj}

The analyst expresses the utilities U_{nsj} of the choice alternatives as functions V_{nsj} of the observable attributes of alternatives X_{sj} and observable characteristics of the individual Z_n; plus random error components ϵ_{nsj}, which include unobserved utility components and stochastic errors:

$$U_{nsj} = V_{nsj}(X_{sj}, Z_n) + \epsilon_{nsj} \tag{5.1}$$

These error components reflect the fact that the analyst cannot observe an individual's utility directly, and make the utilities random variables, hence the term "random utility". The presence of the error terms also means that the analyst, using random utility maximisation (RUM) theory, can at best predict the *probability* for the choice of an alternative, but cannot predict deterministically the choice outcome. According to RUM theory, the choice probability for alternative i belonging to the choice set J_{ns} is given by:

$$P_{nsi} = \Pr\left[V_{nsi} + \epsilon_{nsi} \geq V_{nsj} + \epsilon_{nsj}\ \forall j \in J_{ns}, j \neq i\right] \tag{5.2}$$

In order to calculate these choice probabilities, assumptions regarding the distributions of the error terms are therefore required. Specific distributional choices lead to different models.

5.2.2 Estimation

The most widely used estimation procedure for discrete choice models is maximum likelihood estimation. Given a sample of $\sum_n^N S_n$ observed choices from N individuals, the likelihood function to be maximised is given by:

$$L = \prod_{n=1}^{N} \prod_{s=1}^{S_n} \prod_{j \in J_{ns}} P_{nsj}^{y_{nsj}}(\eta) \tag{5.3}$$

where η a vector of unknown parameters specifying the functional form of the systematic utility and the error terms; y_{nsj} is an indicator equal to 1 if individual n has chosen alternative j in choice situation s, zero otherwise.

5.2.3 MNL

The MNL model was introduced in Chapter 2, where EV adoption models are discussed (section 2.3.1), as it is widely used in the modelling of vehicle type choice. Indeed, the MNL is the workhorse of discrete choice analysis. The reason for its widespread use is the fact that in the MNL model choice probabilities are obtained in a closed form as a function of the systematic utility of the discrete choice alternatives. The logit formula was initially derived by Luce (1959) from the assumption of *independence from irrelevant alternatives* (IIA). Later, Marshank (1960) demonstrated that the logit was consistent with random utility maximisation. Finally, McFadden (1974) demonstrated that the logit formula for choice probabilities implies that the unobserved utility is necessarily a distributed extreme value.

CHOICE PROBABILITIES AND THE IIA PROPERTY

The logit probabilities, derived from the assumption that the unobserved utilities are independently and identically distributed (IID) extreme value type I, for choosing alternative $i \in J_{ns}$ are given by the formula:[36]

$$P_{nsi} = \Pr(i|\, W_{ns}, \eta) = \frac{\exp\,(V_{nsi}(X_{si}, Z_n, \eta))}{\sum_{j \in J_{ns}} \exp\,(V_{nsj}(X_{sj}, Z_n, \eta))} \tag{5.4}$$

The main characteristic of this model, the IIA property, is evident when taking the ratio between the probabilities of two alternatives. This ratio depends only on those two alternatives, therefore it is unaffected by the introduction of a further alternative in the choice set, and by changes in the attribute values of other alternatives in the choice set. This means that, between these two alternatives, the rate of substitution is unaffected by changes in the rest of the choice set. This property is realistic when one can be confident that alternatives in the choice set do not share a correlation in their unobserved utilities. When they do, one should expect disproportionate changes in probabilities due to the introduction of a new alternative in the choice set or due to changes in attribute levels. In section 2.3.1 of Chapter 2, where the use of discrete choice models vehicle type choice is reviewed, it is discussed how the IIA property may induce unrealistic substitution when the MNL is used to model the introduction of electric vehicles in the automobile market. Several model structures that can be used to relax the IIA property (e.g. generalised extreme value models and mixed logit models) are also mentioned.

In this study, for the choice amongst alternative charging strategies and tour timing, the use of a simple MNL model specification causes a likely reduced realism in the substitution patterns between alternatives as imposed by the IIA property. Indeed, alternatives with similar charging durations, similar available energy levels or similar tour timings are likely also to share unobserved attributes. Thus, changes in the charging costs, resulting for example from changes in tariff structures, are likely to induce a higher variation in the substitution rates between alternatives with similar levels in the non-cost attributes. The IIA property does not allow us to capture this effect.

[36] For a derivation see for example Train (2009)

Acknowledging the limitations of the MNL model as discussed above, we adopt it for the sake of simplicity and because it is deemed sufficient for an exploratory analysis of tastes for the attributes defining a charging option. In chapter 6, in which an application of the modelling framework developed in Chapter 3 is demonstrated in simulation, the MNL model structure is also utilised, leaving the implementation of models accommodating more flexible substitution patterns to future work.

LOG-LIKELIHOOD FUNCTION

As mentioned earlier, discrete choice models are estimated by maximisation of the likelihood function. In fact, equivalently, the negative of the logarithm is usually minimised. The log transformation of the likelihood function (the log-likelihood) for the logit is given by:

$$LL(\eta) = \sum_{n=1}^{N} \sum_{s=1}^{S_n} \ln \frac{\exp\,(\widetilde{V_{ns}})}{\sum_{j \in J_{ns}} \exp\,(V_{nsj}(X_{sj}, Z_n, \eta))} \tag{5.5}$$

where $\widetilde{V_{ns}}$ is the utility of the chosen alternative for individual n in choice situation s. Note that in expression (5.5) the tilde (~) over the systematic utility indicate that this is calculated for the chosen alternative.

5.2.4 Mixed logit

The IID assumption for the logit model does not allow us to capture potential correlation across alternatives, or across choice situations, or to account for random taste heterogeneity. The use of the mixed logit model enables us to overcome these limitations.

The mixed logit can be derived under a variety of behavioural assumptions. For instance, it can be derived assuming an error structure that allows representation of closable flexible substitution patterns (error component logit), or by assuming that utility coefficients are randomly distributed to capture random taste variation. The mixed logit definition is, however, purely based on the functional form of the choice probabilities.

Specifically, mixed logit probabilities are logit probabilities integrated over the density f of one or more utility parameters that instead of being fixed are randomly distributed (over individuals, alternatives or choice situations).

Let the utility functions for the choice alternatives be specified in terms of a set of fixed parameters η and a set of random parameters $\gamma \sim f(y)$:

$$U_{nj} = V_{ni}(X_j, Z_n, \eta, \gamma) + \nu_{nj} \tag{5.6}$$

where, for exposition purposes, only a single choice situation per decision maker is considered. Assuming that ν_{nj} IID extreme value type I across alternatives and decision makers; then we can write logit probability L_{ni} for choosing alternative i conditional on parameters γ as:

$$\Pr(i|X_{ni}, Z_n, \eta; \gamma) = L_{ni} = \frac{\exp\,(V_{ni}(X_i, Z_n, \eta, \gamma))}{\sum_{j \in J_n} \exp\,(V_{nj}(X_j, Z_n, \eta, \gamma))} \tag{5.7}$$

Then the unconditional probability is obtained as:

$$\Pr(i|X_{ni}, Z_n, \eta) = \int_{\Gamma} L_{ni} f(\gamma)\, d\gamma \tag{5.8}$$

where Γ is the support of $f(\gamma)$. Equation (5.8), defines the mixed logit model, as a mixture of logit probabilities.

This model structure is extremely flexible. Indeed McFadden and Train (2000) have shown that it can approximate any random utility model: in this way it can be used to overcome the aforementioned limitations of the logit model.

In this chapter, mixed logit is used to capture variability in the marginal utilities for the charging attributes, therefore we briefly present its derivation here under the hypothesis of random variability in the utility coefficients.

RANDOM COEFFICIENTS

Consider again decision makers facing a single choice each amongst N_{J_n} alternatives belonging to choice sets J_n.

Let, for simplicity, the utilities for the alternatives be specified as linear-in-parameters. Let β_n be a *K*x1 parameters' vector. Subscript *n* indicates that these vary across the decision makers. Let also β_n be distributed across the decision makers' population with density $f(\beta_n)$.

Let U_n be $N_{J_n} \times 1$ vector of the utilities for the alternatives, and X_n the $N_{J_n} \times K$ matrix of observed variables that are used to specify the systematic utility (alternatives' attributes and individual characteristics). The vector form of the model's utilities is therefore given by:

$$U_n = X_n \beta_n + \nu_n \tag{5.9}$$

where ν_na $N_{J_n} \times 1$ vector of extreme value type 1 IID random errors. The logit probabilities conditional on β_n for alternative i can be obtained using expression (5.8). The unconditional probabilities are then given by integration over the density$f(\beta_n)$.

The vector form is useful when dissecting the component of U_n to highlight the specific components of β_n under the assumption of normally distributed coefficients. Let $\beta_n \sim N(\beta, \Omega)$ then it is possible to show that

$$U_n = X_n \beta + X_n \Lambda \zeta_n + \nu_n \tag{5.10}$$

where Λ is a lower triangular matrix that is the Cholesky factor of Ω and ζ_n is a $K \times 1$ vector of IID standard normal errors. When the coefficients are specified to be uncorrelated, Λ is a diagonal matrix and its elements are the standard deviations of the coefficients.

While in expression (5.10) the random coefficients are assumed to be normally distributed, this need not be the case. In fact, one of the key issues when estimating mixed logit models is the choice of the underlying distribution. The most common choices are: normal, lognormal triangular and uniform distributions (Hensher and Greene, 2003). More flexible distributional forms have also been proposed and used (Hess et al., 2005, Train and Sonnier, 2005).

Positive support distributions are preferred when the response parameter needs a specific sign to be behaviourally plausible (e.g. positive cost coefficients arguably do not have behavioural meaning). It should be pointed out that although the use of the normal distribution indeed implies an “incorrect” sign of parameters in part of the population, it has been argued that this might not be a complete drawback, since it allows identification of the existence of outliers, coding errors or departures from compensatory theory (Ortuzar and Willumsen, 2011).

In fact, the practical approach is to select distributions that give the analyst a “sense that the *empirical truth* is somewhere in their domain” (Hensher and Greene, 2003). Hensher and Greene (2003) suggest revealing the empirical distribution using a *jack knife-like* technique. (Fosgerau and Bierlaire, 2007) propose a semi-non-parametric approach to test the mixing distribution choice.

In the application in this chapter the choice of normally distributed coefficients is purely based on convenience. In fact, the purpose of using the mixed logit here is to gauge the size of the residual unobserved variability in charging choice attributes when part of the systematic variability has already been unearthed.

MAXIMUM SIMULATED LIKELIHOOD ESTIMATION

Considering the general mixed logit probabilities in equation (5.8), and assuming the parametric distribution $f(\gamma|\theta)$ for the parameters γ, the log-likelihood function for the mixed logit model is given by:

$$LL = \sum_{n=1}^{N} \sum_{j \in J_n} \ln\left(y_{nj} \int_{\Gamma} L_{nj} f(\gamma|\theta)\, d\gamma \right) \tag{5.11}$$

The integral in the expression above does not have a closed form but it is typically approximated using simulation as:

$$SP_{nj} = \frac{1}{R} \sum_{r=1}^{R} L_{nj}(\gamma = \gamma_r) \tag{5.12}$$

where γ_r is a single draw from $f(\gamma|\theta)$ out of a total of R draws. SP_{nj} is an unbiased estimator of the integral in equation (5.11), i.e. of the mixed logit probability.

Simulated probabilities SP_{nj} are substituted in equation (5.11) in place of the integrals, generating the simulated log-likelihood. This is then the function that needs to be maximised to obtain estimates of η and θ. These are, respectively, the fixed utility parameter estimates (those assumed to be fixed across individuals) and the estimates of parameters defining the shape and scale of the distribution of those utility parameters assumed to be varying randomly across individuals.

The derivation of the log-likelihood above was obtained based on the assumption of a single observation from each sampled individual. Revelt and Train (1998) developed a framework that is able to accommodate repeated choices by the same decision maker, as is the case for the choice experiments in this study and, in general, in most stated choice studies. Assuming that the random parameters vary across decision makers but are constant for all choice situations faced by a single decision maker, the probability that decision maker n is observed to make the sequence of choices $I_n = \{i_1, \ldots I_{S_n}\}$ is:

$$P_{I_n} = \Pr(I_n | X_{ni}, Z_n, \eta) = \int_{\Gamma} \left[\prod_{s=1}^{S_n} L_{ni_s} \right] f(\gamma|\theta) d\gamma \qquad (5.13)$$

As the product of conditional probabilities is within the integral, the unconditional probability for the choice sequence is simulated as:

$$SP_{I_n} = \frac{1}{R} \sum_{r=1}^{R} \prod_{s=1}^{S_n} L_{ni_s}(\gamma = \gamma_r) \qquad (5.14)$$

Now, let $\widetilde{I_n}$ be the sequence of choices of individual n observed in an estimation sample, and $SP_{\widetilde{I_n}}$ the corresponding simulated probability (here the tilde ~ indicates the choice sequence that is actually observed in the estimation sample). Then the simulated log-likelihood for the observed choice sequences in the sample is

$$SLL = \sum_{n=1}^{N} \ln SP_{\widetilde{I_n}} \qquad (5.15)$$

The expression of $SP_{\widetilde{I_n}}$ can be written as:

$$SP_{\widetilde{I_n}} = \frac{1}{R} \sum_{r=1}^{R} \left[\prod_{s=1}^{S_n} \widetilde{L_{ns}}(\gamma = \gamma_r) \right] \qquad (5.16)$$

where $\widetilde{L_{ns}} = \prod_{j \in J_{ns}} (L_{nsj})^{y_{nsj}}$ is the logit formula for the chosen alternative calculated for $\gamma = \gamma_r$ (note that the tilde ~ here indicates that the logit formula is calculated for the chosen alternative by individual n in choice situation s in the estimation sample).

The simulated log-likelihood above is valid if the random parameters are fixed across choice situations for the same individuals. In the case of random coefficient mixed logit, this implies that the taste of an individual does not vary from one choice situation to another. This hypothesis of intra-individual homogeneity is usually adopted in the case of repeated choices in choice experiments and, accordingly, this hypothesis is also adopted in the analyses presented later in this chapter. It should be pointed out, however, that it has been questioned, for example by Hess and Rose (2009), who propose a method to accommodate intra-respondent heterogeneity in random coefficients and to derive the expression for the model simulated log-likelihood.

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5.2.5 Integrated choice and latent variable models

Over the last decade considerable effort has been put into explicitly incorporating into choice models the psychological factors affecting decision making. The Integrated Choice and Latent Variable Model (ICLV), as part of the general Hybrid Choice Modelling (HCM) framework, enables the inclusion of attitudes, opinions and perceptions as psychometric latent variables, in order to explain individual choice processes and, possibly, increase the predictive power of choice models (Ben-Akiva et al., 2002). Hybrid choice models have been used in several fields including, increasingly, in transport demand modelling, in order to take into account aspects of choice behaviour that the traditional random utility framework of discrete choice models does not accommodate: primarily the effect of unobservable individual characteristics such as attitudes. A few applications of hybrid choice models in the context of electric vehicle or alternative vehicle fuel choices were mentioned in Chapter 3. They have also been widely applied, for example, to account for environmental attitudes, flexibility, comfort, convenience, safety, and security in travel choices. Daly et al. (2012) report a summary of studies making use of ICLV models. Moreover, HCM have also been applied to deal with missing or poorly measured variables (Hess et al., 2013).

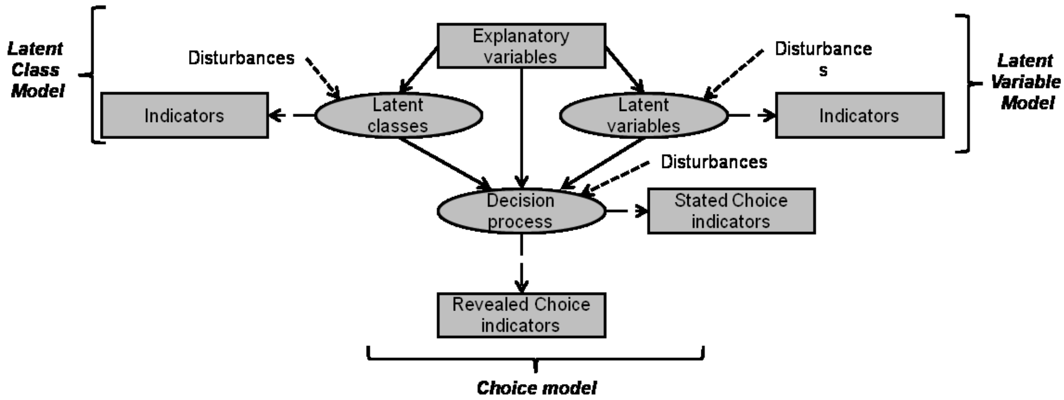

Figure 19: The hybrid choice model conceptual framework, (Ben-Akiva et al., 2002).

The general conceptual framework of hybrid choice models is presented in Figure 19 above. This encompasses extensions to standard discrete choice models such as:

- heterogeneity by means of flexible error structures (of which the random coefficients mixed logit is a special case);
- latent classes that explain market segments;

- the integrated choice and latent variable model which takes into account those constructs (e.g. attitudes, and attributes such as safety or comfort) that are difficult to measure objectively or precisely;
- the presence of unobserved decision protocols (not necessarily based on compensatory theories).

Of this complex framework we are specifically interested in the integrated choice and latent variable model component utilised in this chapter.

Figure 19 shows that, since latent variables are unobserved constructs, they manifest themselves only through indicators. Typically these indicators are obtained by asking specific attitudinal questions of the survey respondents. Such indicators inform the latent variables, and, in turn, the latent variables affect the decision process: if a random utility framework is adopted, we say that these affect the utilities of the alternatives.

Mathematically, an ICLV model is defined by the following set of structural and measurement equations (Bolduc and Daziano, 2008):

Structural equations

The structural equation that relates the (latent) utilities for the choice alternatives to exogenous attributes of alternatives and an individual's characteristics and to the latent constructs X_n^* affecting the utility is:

$$U_{nj} = V_{nj}(X_j, Z_n, X_n^*, \eta) + \nu_{nj} \tag{5.17}$$

where X_n^* is the vector of latent variables. ν_{nj} is assumed to be IID extreme value type one, if a logit kernel specification is chosen. A Logit kernel is a discrete choice model that has both probit-like, (i.e. normally distributed), disturbances as well as an additive i.i.d. extreme value type I disturbance, i.e. "logit kernel" is an alternative terminology for mixed logit. It should be noted that other discrete choice models, e.g. probit, could also be chosen for the choice model part of the ICLV[37].

[37] If the error terms ν_{nj} are specified multivariate normal, the discrete choice model part of the ICLV is a multinomial probit model. Indeed, a multinomial probit model is a random utility discrete choice model derived under the assumptions that the unobserved utility components (i.e. the error terms) are

Latent variables are in turn usually specified linearly in terms of individual characteristics as follows:

$$X_n^* = \Gamma Z_n + \omega_n, \omega_n \sim N(0, \Sigma_\omega) \tag{5.18}$$

where Γ is a matrix of parameters to be estimated. A normal distribution is usually assumed for the error components ω_n.

Measurement equations

Both the utilities and the latent variables are measured through indicators: i.e. the choice outcomes and specific latent variable indicators respectively. Measurement models provide the link between choice outcomes and utilities; and between latent variables and their indicators.

For the utilities, the measurement model is:

$$y_{ni} = \begin{cases} 1 & U_{ni} \geq U_{nj}, \forall j \in J_n, j \neq i \\ 0 & otherwise \end{cases} \tag{5.19}$$

For the latent variables, the measurement model is typically specified as linear (Walker, 2001, Bolduc and Daziano, 2008, Daly et al., 2012):

$$Y = \theta_0 + \Theta X_n^* + \epsilon_n, \epsilon_n \sim N(0, \Sigma_\epsilon) \tag{5.20}$$

where θ_0 is a vector of constants and Θ a matrix of the coefficients to be estimated.

If the indicators are not continuous (e.g. they are discrete or ordinal), discrete (ordered) regressions models can be specified for the measurement model.

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jointly normal. As briefly mentioned in section 2.3.1 when reviewing choice models for vehicle adoption, the probit models can be specified to handle random taste variation, flexible substitution patterns and can be applied to panel data with temporally correlated errors. These features can be obtained as well using mixed logit models, which are in fact the appropriate choice when restrictions on the support of the distribution are required. For example, when modelling random taste variation in a price coefficient, a mixed logit allows specifying a price coefficient distribution with positive support (e.g. lognormal): in a probit model this is not possible (Train, 2009).

The model components above can be estimated simultaneously using maximum likelihood estimation, having expressed the joint likelihood for choice outcome and latent variable indicators. We do not provide the expression here for the general model above, but the expression of the choice probabilities and the joint log-likelihood for the specific application in this study is provided in section 5.4.

5.2.6 A note on identification and normalisation

Identification and normalisation issues in traditional discrete choice models are nowadays well understood. In the interests of brevity, these are not discussed here: the interested reader is referred to the relevant literature (Ben-Akiva and Lerman, 1985b, Walker, 2001, Train, 2009). In contrast, general necessary conditions have not been developed for the identification of hybrid choice models (Bolduc and Daziano, 2008). The standard procedure is to ensure that all the model components are identified separately.

Concerning specifically ICLV models in the literature two alternative methods have been proposed, respectively, by Ben-Akiva et al. (1999a) and Bolduc et al. (2005), for the normalisation of the latent variable measurement model component. Both approaches are intended for the normalisation of the scale of the measurement model. In the presence of multiple indicators, the Ben-Akiva normalisation strategy normalises the impact of a latent variable for one of the indicators. The Bolduc normalisation strategy, meanwhile, normalises the variance of the error term of the latent variable structural equations to 1. In our analyses we adopt the Bolduc normalisation strategy so that the sign of the impact of the range anxiety on its indicator can be verified.

In order to verify empirically that the model is identified we also undertake several of the empirical identification tests suggested by (Walker, 2001).

5.3 Analyses of choice experiment 1

This section provides the details of the discrete choice model specifications adopted for the analysis of choices from SCE1 as well as the analyses' results and discussion. The present section is structured as follows:

- Firstly (in subsection 5.3.1), the description of the choice situation is briefly recalled as an aid to the reader. A base specification for the utility of the alternative s in the choice experiment is also given.
- Secondly (in subsection 5.3.2), general hypotheses regarding the charging choice taste parameters are provided. Potential sources of systematic taste heterogeneity are also discussed.

- Thirdly (in subsections 5.3.3 to 5.3.5), base specification estimates are provided, and diagnostic model estimates are presented in order to investigate those results for the base specification that were found to partially contradict general hypotheses.
- Finally (in subsections 5.3.6), results from a model accounting for systematic taste variations are presented and discussed.

5.3.1 Choice experiment 1 description and specification of base model

In SCE1, ECarSim respondents were told to consider a home based tour extracted from their travel diary, and to choose their preferred option from two alternatives. Respondents were informed that there are no charging facilities available at any of the tour stops. The charging alternatives were presented, as in Figure 20, in terms of battery/energy/range interval levels after charging, charging duration and cost; along with the battery level before charging ("the initial battery level") and the charging operation's start time. In SCE1, the charging operation duration is always within the vehicle dwell time at home that was originally observed in respondents' travel diaries: i.e. there are no charging alternatives causing schedule delays.

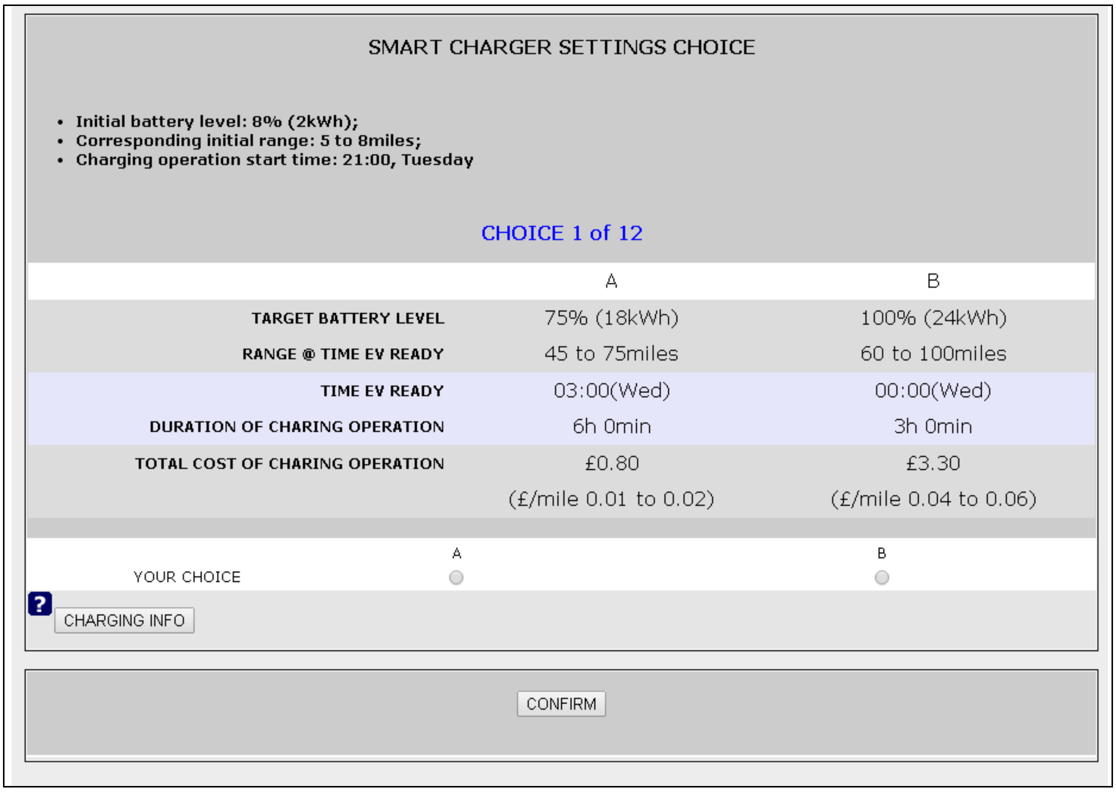

Figure 20 An example of a choice task from choice experiment 1 of ECarSim

The purpose of SCE1 is to obtain estimates of the taste parameters for the available energy after charging, the charging duration and the cost, and to analyse the relative effects of these three attributes characterising a charging option. Based on the modelling framework developed in subsection 3.4.2, the utility of a charging option, (when no schedule delay is induced by the charging operation) is expressed as:

$$U_{isn} = \alpha_i + \beta_E E_{nsi} + \beta_{CT} CT_{nsi} + \beta_{CC} CC_{nsi} + \epsilon_{nsi} \tag{5.21}$$

where n denotes the individual undertaking the choice and s the choice situation. As in the previous chapters, E denotes the available energy stored in the battery after charging; CC the costs for charging; and CT the charging duration. Recall that CT is intended to be the elapsed time since the arrival at the (home) charging facility until the target battery level has been reached. β_E, β_{CT} and β_{CC} are the respective taste parameters. α_i is the alternative specific constant (ASC), because in SCE1 the choice is unlabelled, the ASC should only capture the effect of the position of the alternative. ϵ_{nsi} is an error term.

5.3.2 Hypotheses on charging choice taste parameters and systematic taste heterogeneity sources

GENERAL HYPOTHESES FOR AVAILABLE ENERGY AND CHARGING DURATION TASTE PARAMETERS

The following two general hypotheses are made for the charging option parameters:

- A positive sign for the taste parameter β_E,
- A negative sign for the taste parameter β_{CT}.

The first hypothesis reflects the intuitive idea that a higher available range is preferred, since higher available energy entails a higher available range. The second reflects the idea that, all else being equal, faster charging operations are preferred.

EV purchase studies have found evidence for preferences for higher ranges (Bunch et al., 1993, Golob et al., 1997b, Ewing and Sarigöllü, 1998, Brownstone et al., 2000a, Dagsvik et al., 2002) and shorter charging durations (Ewing and Sarigöllü, 1998). Available energy and charging duration taste parameters have not been estimated in the context of charging choices, however (i.e. in a tactical choice context rather than in a strategic one such as that of vehicle purchase choices).

In the strategic context of car purchase choice higher ranges and shorter charging duration preferences may reflect option values. Although typical travel patterns are compatible with a typical full charge range of electric cars (100 miles) and a typical charging durations of 8 hours, drivers choosing their new car value the option to be able to use it even for very infrequent journeys beyond 100 miles, or in (emergency) situations when faster charging may be needed.

In tactical charging choices, in contrast, the specificity of the choice context may strongly affect the preferences for available range (i.e. available energy) and for the charging duration. Such preferences are, therefore, likely to be more heterogeneous in the charging choice contexts. For this reason, it is interesting to assess how such preferences are affected both by individual characteristics and by the characteristics of the prospective travel to be undertaken after charging.

POTENTIAL SOURCES OF SYSTEMATIC VARIATION IN MARGINAL UTILITIES OF CHARGING ATTRIBUTES

The systematic utility specification shown in equation (5.21) represents a base specification. In order to capture systematic variation in the taste parameters, interaction terms between individual or tour characteristics and the charging option attributes can be added. The following considerations were adopted in order to specify interaction terms.

Tour characteristics potentially affecting the utility for available energy after charging

The main variable affecting the utility of available energy is deemed to be the travel distance after charging. Increasing the travel distance may increase the associated (perceived) uncertainty regarding the occurrence of potential travel disruptions that may require higher driving ranges.

In the choice experiments the travel distance is also associated with ambiguity in tour feasibility (see subsection 4.8.1). For example, considering the choice situation in Figure 20, a distance of 50 miles for the prospective home-based tour after charging would make *alternative A* ambiguous in terms of tour feasibility, whereas *alternative B* would guarantee the feasibility of a 50 miles tour.[38]. It is anticipated that when expecting to drive longer distances individuals tend to reduce this ambiguity by preferring higher available energies after charging.

In addition, tour purpose may also affect the utility for available energy. For work or other mandatory activities, one may expect a preference for higher available energy, reflecting a lower propensity to risk of failing to reach the destination of these types of activities.

Tour characteristics potentially affecting the utility for charging duration

[38] This definition of ambiguity in tour feasibility clearly applies under the assumption that respondents trust the information that is provided.

Given that in SCE1, the tour timing is not disrupted by the duration of the charging operation, it is difficult to make specific hypotheses regarding the potential effects of the prospective tour characteristics on the taste for charging duration. Nevertheless, intuition suggests that tour types that may entail an option value for earlier departure times with respect to a reference plan may induce a preference for shorter charging durations. For example, drivers knowing that they will have to travel at times of high traffic, i.e. low travel time reliability, may need to revise their departure time plan once the charging operation is ongoing, in order to respond to new available information regarding travel times. Such newly available information may require them to leave earlier than planned, and therefore they might have a higher preference for having their vehicle ready to use in shorter times.

The hypothesis above can be tested by the introduction into the utility specification of an interaction term between charging duration and a dummy indicating that the time of travel for the outbound leg of the planned tour is in peak traffic hours.

In addition, the existence of potential variability of taste across tour purposes is tested by interacting tour purpose dummy variables with charging duration. No specific *a priori* hypotheses are made regarding the potential signs of the effects, however, and therefore the results should be regarded as purely exploratory.

Individuals' characteristics for systematic heterogeneity specification

Concerning demographics, *a priori* hypotheses regarding their effect on the available energy and charging duration parameters are difficult to make. It is possible that such variations reflect the effect of unobserved attitudes that are likely to characterise homogeneous groups of individuals. On the other hand, it is reasonable to expect that income, or variables associated with it, may affect the cost coefficient.

Although the relationship between demographics and available energy or charging duration may not be intuitive, it can provide directions for further investigation of specific hypotheses in future work. Moreover, capturing systematic heterogeneity using variables such as population demographics gives a model the possibility to be used in forecasting, whereas attitudinal information is not in general available for the forecasted population, unless explicitly modelled.[39]

Individual characteristics which are included in interactions with E, CT and CC are:

- Gender;
- Age group;
- Employment status (employed / not employed);
- Education level (higher level / lower level), where "higher" identifies the group of individuals having obtained one of the following higher education qualifications:
  - University Higher Degree (e.g. MSc; PhD);
  - First degree level qualification (e.g. BA; BSc; PGCE).
  - Diploma in higher education; HNC, HND, Nursing or Teaching qualification (excluding PGCE).

Income was not included as it was affected by item non-response; however it was correlated with age, as expected. Table 9 and Table 10 show the cross tabulation and associated statistics of two income groups with the two age groups, for all cases not affected by item non-response.

Table 9: Cross-tabulation between household income groups and age groups in the ECarSim dataset

Age level X Income level Crosstab				
		Income		Total
		£0-£29,999	£30,000+	
Age 2 levels	20-35	14	20	34
	36+	4	32	36
Total		18	52	70

39 Integrated choice and latent variables models belonging to the general class of hybrid choice models indeed allow us to model the effects of attitudes on choices without the necessity to specify directly the attitude indicators into the systematic utility specification, by making use of a structural model for latent variables underlying the attitudes. The estimation of such models does require attitude indicators, but, in principle, model application in forecasting just requires exogenous variables by which the latent variable structural model is specified, which are typically individual characteristics generally available in the forecasted population.

Table 10: Association statistics between age groups and income groups in the ECarSim dataset

Age level X Income Chi-Square Tests					
	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	8.274[a]	1	.004		
Continuity Correction[b]	6.775	1	.009		
Likelihood Ratio	8.621	1	.003		
Fisher's Exact Test				.006	.004
Linear-by-Linear Association	8.156	1	.004		
N of Valid Cases	70				
a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 8.74.					

The effect of household composition variables was tested in preliminary analyses, but it did not significantly affect any of the charging attributes. These variables are, therefore, excluded from the analyses presented in this section.

Summary of tour and individual variables used to model systematic taste variations

Table 11 reports a summary of the individual and tour characteristics investigated as potential sources of systematic variations in taste for the charging operation attributes.

Table 11 Variables used to specify systematic taste variations

Individual/ tour characteristic	Dummy variables	Notes
Gender	Female	-
Age groups	Age 20-35 Age 31-55 Age 56+	
Employment status	Employed	Indicates individual in employment
Education level	No university	Indicates individuals not holding any University or Higher education diploma
Tour distance	Distance 30-40 miles Distance 41-50 miles Distance 51-60 miles Distance 61+ miles	
Tour purpose	Leisure/Social tour purpose Work tour purpose Education tour purpose Other tour purpose	
Tour timing	Travel in peak periods	Indicates that the outbound leg of the tour occurs at least partially in periods 7-9am or 4-6pm

5.3.3 Base specification estimates

Consider first the base specification in equation (5.21). MNL estimates for the parameters, β_E and β_{CT}, β_{CC} are provided here in Table 12.

Table 12: Charging choice model, choice experiment 1– base specification

Variables in model (*)	coefficient	st-err	t-stat
A	0	fixed	***
B	-0.0431	0.0647	-0.6660
E [kWh]	0.0791	0.0143	5.5445
CT [10h]	0.0347	0.0499	0.6963
CC [£]	-0.3008	0.0374	-8.0405
N parameters	4		
N individuals	88		
N observations	1056		
Null log-likelihood	-731.9634		
Final log-likelihood	-691.7909		
Likelihood ratio index, ρ	0.0549		
Adjusted likelihood ratio index, ρ_{adj}	0.0494		

(*) Appendix D provides reference tables with the definitions of the variables

The overall fit of the model is poor as the likelihood ratio index[40] ρ low value shows. This may suggest a large variability across individuals in the utility parameters and also non-linearity may play a strong role. Other potential reasons include omitted variables or non-compensatory choice behaviour.

Only the available energy and the cost coefficients have the expected sign (positive and negative respectively) and are significant. The charging duration attribute is positive and not significant. This model, therefore, only confirms the expectation of preference for higher available energy, suggesting that higher ranges are preferred when charging EVs.

[40]The statistic called the likelihood ratio index statistic is often used to measure the goodness of fit of a model. It is defined as $\rho = 1 - \frac{LL(\beta)}{LL(0)}$, where $LL(\beta)$ is the log-likelihood calculated wth the estimated parameters at convergence (also called final log-likelihood) and $LL(0)$ is the null log-likelihood, that is the log-likelihood calculated when all parameters are set to zero. More specifically it measures how a model performs compared to a model with all parameters equal to zero. If ρ is equal to zero the model with estimated parameters does no better than a model with parameters fixed to zero, which in a linear-in parameter specification means that the model does no better than a model assigning equal probabilities to all choice alternatives. On the other hand a model that would predict perfectly the sample decision maker choice would have a likelihood equal to 1 and a log-likelihood equal to zero, thus a ρ equal to 1. Therefore, the closer ρ is to 1 the higher the goodness of fit of the model. To compare the goodness of fit with a different number of parameters, penalising the less parsimonious specification, the adjusted rho index is used: $\rho_{adj} = 1 - \frac{LL(\beta)-K}{LL(0)}$, where K is the number of estimated parameters.

The lack of statistical significance and the unexpected direction of the charging time parameter might be explained by a combination of factors:

- Attribute non-attendance
- Correlations amongst attribute levels, caused by constraints introduced in the experimental design,[41] to avoid:
    - alternatives with unfeasible charging powers (i.e. with $(E - E_0)/CT$ exceeding 7.2 kW);
    - dominant alternatives.

5.3.4 Diagnostic analysis I: full charge at the fastest speed

The constraints introduced in the experimental design to avoid charging powers above the current limit have introduced perfect collinearity between the maximum level of available energy (24 kWh, corresponding to a SOC of 100%) and the shortest charging time (3 hours) needed to achieve that level from the battery level available before charging (2kWh for all respondents). In total, for each respondent, 6 out of the 12 choice situations faced by the respondent were characterised by at least one alternative with the full charge at the highest charging speed.

In order to account for this we slightly modified the systematic utility by introducing a dummy variable to capture separately a discontinuity in the utility of an alternative characterised by a full charge (at the fastest possible rate). We denominate this variable FFC ("fast full charge"). Therefore, the empirical specification for the systematic utility of a charging alternative in SCE1 becomes:

$$V_{isn} = \beta_{FFC} FFC_{nsi} + \beta_E E_{nsi} + \beta_{CT} CT_{nsi} + \beta_{CC} CC_{nsi} \tag{5.22}$$

[41] See Chapter 4, subsection 4.5.2

Table 13: Charging choice models, experiment 1 data – fast full charge avoidance

Variables in model (*)	coefficient	st-err	t-stats
A	0	fixed	***
B	-0.053	0.065	-0.816
FFC	-0.426	0.162	-2.631
E [kWh]	0.094	0.015	6.114
CT [h]	-0.006	0.006	-1.029
CC [£]	-0.272	0.039	-6.984
N parameters	5		
N individuals	88		
N observations	1056		
Null log-likelihood	-731.963		
Final log-likelihood	-688.320		
Likelihood ratio index, ρ	0.060		
Adjusted likelihood ratio index, ρ_{adj}	0.053		

(*) Appendix D provides reference tables with the definitions of the variables

The FFC dummy coefficient is negative, signalling that individuals, all else being equal, tend to avoid alternatives leading to a (fast) full charge. As a consequence, the available energy coefficient increases in magnitude and statistical significance while the charging duration coefficient becomes negative, as expected (although it remains not significant). These changes are due to the fact that the FFC alternatives consist of the highest possible level for available energy throughout the sample and to a low charging duration value in most of individuals in the sample.

This seems to suggest that, in a considerable share of choice situations, respondents lack the incentive to choose the full and fast alternative. A particular reason why in some instances there is a lack of incentive for choosing the more costly FFC alternative is that, in some choice situations, both alternatives guarantee the tour feasibility *without ambiguity*.[42] It is possible that when both alternatives assure feasibility, (a group of) respondents may find it

[42] The reader may recall from Chapter 4 that an alternative is characterised by ambiguity in tour feasibility if the planned tour is longer than the lower bound of the range interval corresponding to the available energy level for the alternative. For example, considering the choice situation in Figure 20, assuming that the ECarSim respondents were facing this choice before a tour having a 50 miles driving distance, alternative A would be characterised by tour feasibility ambiguity, whereas alternative B would not.

pointless, all else being equal, to charge much above the level guaranteeing tour feasibility. Indeed, in ECarSim, it was not explicitly suggested that the electric car could have been used beyond the tour around which the choice experiments were designed, therefore it is possible that some respondents might not have found it attractive to charge more than what they considered sufficient to complete the tour in the choice experiment.

The effect of choice situations without ambiguity in tour feasibility in any of the two alternatives is shown in subsection 5.3.5, below.

5.3.5 Diagnostic analysis II: choice situations with and without ambiguity in tour feasibility

The observations from the first choice experiment can be separated into two subsamples: one comprising the choice situations in which both alternatives guarantee tour feasibility (301 observations), the other in which at least one alternative does not guarantee feasibility without ambiguity (755 observations).

Table 14 shows the estimates for the subset of observations in which all choice sets contain alternatives without ambiguity in tour feasibility. The base specification shows a negative estimate for the available energy coefficient and a positive one albeit insignificant for the charging duration coefficient. In the specification with the FFC dummy variable the available energy coefficient becomes positive, while the FFC coefficient is large and negative. Both parameter estimates are not greatly significant. It is evident, however, that a subset of respondents tends to avoid the FFC alternative. Since in 44 out of 301 choice situations the high FFC alternative is chosen, it is possible to hypothesise some heterogeneity in the taste for FFC even within this subset, which would explain the low significance of the parameter estimate.

Table 14: Charging choice models, experiment 1 data – analysis of choice situations without ambiguity in tour feasibility

Var. in model (*)	Coeff.	St. err	T-stat	Coeff.	St. err	T-stat
A	0	fixed	***	0	fixed	***
B	-0.029	0.163	-0.180	-0.033	0.164	-0.199
FFC	***	***	***	-3.940	2.619	-1.504
E [kWh]	-0.082	0.050	-1.633	0.422	0.338	1.249
CT [10h]	0.042	0.168	0.252	-0.012	0.171	-0.071
CC [£]	-0.435	0.100	-4.337	-0.421	0.101	-4.184
N of par.	4			5		
N of ind.	51			51		
N of obs.	301			301		
Null Log-lik.	-208.637			-208.637		
Final Log-lik.	-122.444			-121.278		
Likelihood ratio index, ρ	0.413			0.419		
Adjusted likelihood ratio index, ρ_{adj}	0.394			0.395		

(*) Appendix D provides reference tables with the definitions of the variables

Table 15 shows the model estimates for the subset of all choice situations in which the choice set contains at least one alternative that does not guarantee tour feasibility without ambiguity. The base specification shows significant estimates for all three attributes, all with the expected signs. Here the FFC specification shows a significant positive sign for the FFC alternative.

Table 15: Charging choice models, experiment 1 data – analysis of choice situations with ambiguity in tour feasibility

Variables in model (*)	coefficient	st-err	t-stat	Coefficient	st-err	t-stat
A	0	fixed	***	0	fixed	***
B	-0.043	0.082	-0.521	0.010	0.084	0.121
FFC	***	***	***	0.954	0.212	4.498
E [kWh] (base)	0.181	0.019	9.421	0.176	0.020	8.875
CT [10h] (base)	-0.364	0.071	-5.133	-0.213	0.080	-2.674
CC [£]	-0.334	0.050	-6.632	-0.431	0.057	-7.503
N of parameters	4			5		
N of individuals	88			88		
N of observation	755			755		
Null Log-likelihood	-523.326			-523.326		
Final Log-likelihood	-464.394			-453.798		
Likelihood ratio index, ρ	0.113			0.133		
Adjusted likelihood ratio index, ρ_{adj}	0.105			0.123		

(*) Appendix D provides reference tables with the definitions of the variables

These results are consistent with the hypothesis of variation in preferences between choice situations with and without ambiguity in tour feasibility. The estimates in the dataset with ambiguous choice situations reflect an intuitive behaviour. Instead, the negative sign for the

FFC parameter estimates from the other subsample is counterintuitive. As mentioned in section 5.3.4, this might be the result of the specific characteristics of the hypothetical setting, in which only the tour right after the charging operation is emphasised, potentially leading some respondents in the subset to consider it pointless (or wasteful) to charge much above the level guaranteeing tour feasibility. When both alternatives guarantee tour feasibility this group of individuals may, therefore, prefer the option with lower available energy after charging. Although satisfactory explanations for this counterintuitive preference were not found, an hypothesis could be that they may reflect underlying unobserved attitudes, for example towards the environment. For instance, respondents with strong environmental attitudes may consider it wasteful to charge above what is strictly necessary, and they could be willing to pay more to avoid wasteful energy consumption. The lack of attitudinal indicators in the ECarSim dataset makes it impossible to test this hypothesis, however.

In any case, any possible behavioural insight underlying the effect of ambiguity, or lack thereof, in charging choices needs to be further investigated, possibly through both stated and revealed preference settings. In future data collection campaigns, in addition to quantitative data collection, qualitative interviews may help to shed light on this unexpected finding.

We finally present in Table 16 an MNL estimation in which the full sample is used for estimation, taking into account, however, the effect of ambiguous and unambiguous choice situations (unrestricted model). This is done by including interaction terms between all choice attributes and a dummy variable indicating the absence of ambiguity in tour feasibility in both alternatives of the choice situation (we refer to this dummy variable as NACS: as in *no ambiguity in choice situation*). Estimates of course reflect what was found in the analyses with separate subsets. In choice situations without ambiguity there is a tendency to avoid the FFC, whereas the opposite occurs for the other choice situations. Note, however, that this effect is only significant with a 10% significance. In particular, the coefficients' interaction terms with available energy and charging duration and charging cost are not significant. This suggests that a restricted model could be specified in which all the coefficients of the interaction terms are set to zero, except for the FFC's. The results of the restricted model are also presented in Table 16. A likelihood ratio test can be used to verify if the null hypothesis corresponding to the restricted model is rejected. The test statistic is $R = -2(LL_{restricted} - LL_{unresttricted}) = 1.994$. This statistic is asymptotically χ^2-distributed with three degrees of freedom[43] and, therefore, the critical value for a 95% level of confidence is 7.81. Because R is lower that the critical value, the null hypothesis cannot be rejected and thus the restricted model is retained. The large improvement in goodness of fit in this model should be noted; compared to the base specification, where the difference in choice behaviour between ambiguous and unambiguous choice situations was not taken into account.

Table 16: Charging choice models, experiment 1 data – accounting for the effect of choice situations without ambiguity in the full SCE1 dataset

Variables in model (*)	**Unrestricted model**			**Restricted model**		
	Coeff.	Std err	t-test	Coeff.	Std err	t-test
A	0	fixed	***	0	fixed	***
B	0.00126	0.0745	0.02	-0.00416	0.0736	-0.06
CC [£]	-0.429	0.0569	-7.54	-0.413	0.0477	-8.65
CC*NACS (no ambiguity in choice situation) [£]	0.00777	0.116	0.07	0	fixed	
FFC	0.951	0.212	4.5	0.975	0.205	4.77
FFC*NACS	-4.88	2.63	-1.86	-3.25	0.251	-12.95
E [kWh]	0.176	0.0198	8.89	0.171	0.0179	9.51
E*NACS [kWh]	0.246	0.339	0.73	0	fixed	
CT [10h]	-0.212	0.0796	-2.67	-0.168	0.0693	-2.42
CT*NACS [10h]	0.201	0.189	1.06	0	fixed	
Number of estimated parameters	9			6		
Number of observations	1056			1056		
Number of individuals	1056			1056		
Null log-likelihood	-731.963			-731.963		
Final log-likelihood	-575.103			-576.1		
Likelihood ratio index, ρ	0.214			0.213		
Adjusted likelihood ratio index, ρ_{adj}	0.202			0.205		

(*) Appendix D provides reference tables with the definitions of the variables

43 Wilks (1938) demonstrates that as the sample size n approaches to infinity the test statistic

$$-2\log\left[\frac{\sup\{\mathcal{L}(\theta|x_1,x_2,\ldots,x_n),\theta\in\Theta_0\}}{\sup\{\mathcal{L}(\theta|x_1,x_2,\ldots,x_n),\theta\in\Theta\}}\right],$$

where $\mathcal{L}(\theta|x_1,x_2,\ldots,x_n)$is the likelihood function, and sup is the supremum fuction, θ is the parameter of the distribution of variate x over the population. is χ^2 distributed with degrees of freedom (DOF) equal to the difference in the size between the parameters space Θ and its subset Θ_0 defining the null hypothesis. In the specific case discussed here the unrestricted model parameters space Θ has a dimensionality of 9 and the restricted mode parameters' subset Θ_0 has a dimensionality of 6. Therefore, under the null hypothesis (restricted model), the test statistic is asymptotically χ^2 distributed with 9-6=3 DOFs.

The meaning of the restricted model is that unambiguous choice situations affect only the valuation of the full and fast alternative. Although in reality there is no reason to think that such choice situations would not affect charging alternatives with other battery levels and charging durations, this could not be verified using data from SCE1.

5.3.6 Systematic and random heterogeneity in taste for charging attributes

In this subsection the specification restricted model in Table 16 is extended in order to capture systematic taste heterogeneity and random. The individual and tour characteristics that were introduced in subsection 5.3.2 are included in the utility specification in interaction terms with the charging operation attributes. The specification of the systematic heterogeneity was obtained as a result of a specification search that is detailed in Appendix A. Both an MNL model and a mixed logit model are estimated.

For the mixed logit model, the random taste variation is modelled only for the available energy coefficient and the charging duration coefficients. Although for both coefficients there are sign directions that are intuitive (positive for available energy and negative for charging duration), we use a normal distribution mainly for the two following reasons:

- Coefficients of terms interacting with the E and CT simply added to the systematic utility and can be interpreted as heterogeneity around the mean;
- The main purpose of the mixed logit estimation in this case is to observe whether the estimated variances are large and significant when systematic heterogeneity is specified.

It should be noted that the heterogeneity around the mean could also be specified in the presence of lognormal distributions for the random coefficients and that this would preserve their "correct" signs. This entails including the individual and tour variables as multiplicative exponential terms to the lognormal coefficients. This, in turn, causes a considerable increase in the nonlinearity of the utility function that makes it difficult to reach the convergence in the estimation process. Moreover, tests carried out without the interaction terms, using independent lognormal distributions for the two coefficients, lead to unreasonably large variance. Although it is recognised that other positive support distributions are not affected by the latter problem, nevertheless, given that the primary objective is to gauge the size and significance of the residual coefficient variance when systematic heterogeneity is included in the model, normally distributed radon coefficients are deemed to be satisfactory.

The covariance between charging duration and available energy coefficients is also tested in the mixed logit model, as the two random coefficients are not forced to be independent.

Table 17 presents the parameter estimates for the two models. Compared to the MNL model without interaction terms, here, the interactions terms contribute to increasing the model fit (ρ_{adj} grows from 0.202 to 0.297). The largest increase, however, is obtained with the mixed logit specification, which leads to a doubling of the ρ_{adj}.

Table 17: Charging choice models, experiment 1 data – accounting for the systematic and random heterogeneity

	MNL				**Mixed logit**		
Variables in model (*)	Coefficient	st-err	t-stats		Coefficient	st-err	t-stats
A	0	fixed	***		0	fixed	***
B	-0.0083	0.0802	-0.1		-0.0459	0.107	-0.43
CC* [£]	-0.587	0.11	-5.32		-0.77	0.192	-4.02
CC*Employed, [£]	0.296	0.102	2.89		0.083	0.188	0.44
CC*Age 20-35, [£]	-0.338	0.0662	-5.1		-0.368	0.125	-2.93
FFC	0.0185	0.259	0.07		-0.565	0.418	-1.35
FFC* NACS	-2.16	0.312	-6.91		-2.69	0.571	-4.71
E, [kWh]	0.162	0.0244	6.63		0.303	0.0802	3.78
E*Female, [kWh]	-0.0655	0.0243	-2.7		-0.179	0.0845	-2.12
E*Leisure/Social tour purpose, [kWh]	-0.05	0.025	-2		-0.125	0.0922	-1.36
E*Distance 41-50 miles, [kWh]	0.301	0.0413	7.28		0.617	0.144	4.28
E*Distance 51-60 miles, [kWh]	0.323	0.0494	6.55		0.729	0.146	5
E*Distance 61+ miles, [kWh]	0.458	0.0858	5.34		0.88	0.187	4.71
CT, [10h]	-0.0355	0.0905	-0.39		-0.094	0.246	-0.38
CT*No university, [10h]	-0.431	0.129	-3.35		-0.642	0.458	-1.4
CT*travel in peak periods, [10h]	-0.214	0.137	-1.56		-0.186	0.37	-0.5
Covariance matrix elements							
$\begin{Bmatrix} \beta_{E_n} \\ \beta_{CT_n} \end{Bmatrix} \sim N\left(\begin{Bmatrix} \beta_E \\ \beta_{CT} \end{Bmatrix}, \begin{bmatrix} \sigma_E^2 & \sigma_{E,SDL} \\ \sigma_{E,SDL} & \sigma_{SDL}^2 \end{bmatrix}\right)$							
Variance of available energy coefficient β_{E_n}				σ_E^2	0.13	0.0388	3.34
Variance of charging time coefficients β_{CT_n}				σ_{CT}^2	1.5	0.501	2.99
Covariance of β_{E_n} and β_{CT_n}				$\sigma_{E,CT}$	0.224233	0.12	1.88
Number of estimated parameters	15			18			
Number of observations	1056			1056			
Number of Individuals	88			88			
Null log-likelihood	-731.963			-731.963			
Final log-likelihood	-499.547			-411.178			
Likelihood ratio index, ρ	0.318			0.438			
Adjusted likelihood ratio index, ρ_{adj}	0.297			0.414			

(*) Appendix D provides reference tables with the definitions of the variables

SYSTEMATIC TASTE VARIATIONS

The general observation that can be made when considering the model estimates in Table 17 is that both individual and tour characteristics indeed concur in the determination of a significant variability in the marginal utilities for the charging attributes. Specific aspects of this observation are explored below.

Effects on the taste for available energy

- Individuals planning to travel longer travel distances tend to value the available energy level more than others when making their charging choice.
- Individuals planning to undertake leisure or social tours with their EV tend to be less concerned about available energy than others when making their charging choice.
- Women tend to attain a lower utility than men from higher available energy levels.

Apart for the second effect in the list above, all are significant in both the MNL and mixed logit models. The effect of tour purpose becomes insignificant in the mixed logit, which apparently captures part of the variability initially captured by the corresponding interaction term.

It was mentioned before that increasing the travel distance may increase the associated (perceived) uncertainty regarding the occurrence of potential travel disruptions that may require higher driving ranges, so it is perfectly reasonable to observe an increase in the marginal utility for available energy as distance increases.

The lower concern for available energy when expecting to undertake leisure and social tours may reflect the fact that these are not mandatory activities and the consequence of being unable to reach the destination might be perceived as less dire.

The lower level of concern about available energy in women compared to men seems at odds with the interpretation of the charging choice as an uncertain one. Indeed, several studies have found women to be more risk averse than men (Eckel and Grossman, 2008, Dohmen et al., 2011) and, therefore, it should be expected that women would show a lower marginal utility for available energy, which is not the case here. It should be noted, however, that not all evidence supports the somewhat stereotypical view that women are more risk averse (Schubert et al., 1999). Moreover, considering the specific case of choice under ambiguity, evidence also exists that women tend to express the same distaste for ambiguity as men, and in some cases, when the level of ambiguity is small, even less (Borghans et al., 2009).

Effects on the taste for charging duration

The MNL result show a base value not significant, but negative and that

- Individuals not having a university degree or a diploma in higher education are found to value charging duration more negatively than the rest.
- The interaction term between charging duration and travel in peak traffic periods has a negative coefficient, though not very strongly significant.

Both the coefficients for the two interaction terms lose statistical significance in the mixed logit: the second becoming plainly insignificant (t-stat 0.5), the first remaining significant at least at the 0.2 level.

The significant effect of the education level on the marginal utility of charging time is difficult to interpret. Indeed it was included in the model primarily because it contributed to explaining the variability in the charging time coefficient. A possible explanation may be that individuals with a higher level of education may find smart charging more acceptable even though respondents were informed during the survey that, "the smart charger will autonomously control the rate at which the electricity flows into your battery preventing you from being able to exactly predict the battery level at any given time during the charging operation". It may be that those with more education were more likely to view smart charging as a technological advance with potential benefits to society, whereas less educated individuals may consider more strongly the negative effects of limited vehicle availability and the unpredictability of the charging power.

The higher disutility for charging duration when expecting to travel in peak traffic periods may reflect an increased utility in departure time flexibility. Departure time flexibility, guaranteed by shorter charging durations may help to hedge for the limited travel time reliability that may be associated with peak time travel.[44] Note however, as pointed pointed out earlier the coefficient of this interaction terms becomes not significant in the mixed logit model, though it remains negative.

Effects on the cost coefficient

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[44] Travel time variability is indeed associated with increases in traffic in networks characterised by high load, cf. for example Ortuzar and Willumsen (2011).

- The young age group tend to be more cost sensitive.
- Individuals with employment tend to be less cost sensitive (thei effect becomes insignificant in the mixed logit model).

The young age group is associated with the lower income group; therefore it is reasonable to observe increased cost sensitivity.

The fact individuals in employment tend to be less cost sensitive than retired or unemployed seem intuitive; however this effect becomes insignificant in the mixed logit specification. This is probably result of the fact that the low sensitivity to cost of employed individual is also associated this group's sensitivity other attributes[45] captured as random variability in the mixed logit specification.

<u>*Variance and covariance of random coefficients*</u>

Estimated standard deviations are significant and large; the covariance is significant at the (0.1 level).

The standard deviation of the available energy coefficient is large, as it is slightly more than one time the base coefficient, this shows that, a high underlying variability in the marginal utility for available energy, that is not captured by the specification of the systematic heterogeneity. It may be that the residual heterogeneity is random, but it cannot be excluded that other sources of systematic taste variation were not uncovered.

The large standard deviation for the charging duration coefficient combined with the lack of significance of the mean and terms for heterogeneity around the mean shows that there is indeed a large heterogeneity in the way charging duration is perceived. In fact it also shows that the charging duration coefficient varies in sign across the estimation sample. The model implies that there's a large share of individuals having positive marginal utility for charging duration[46]. Preference for longer charging durations is difficult to explain behaviourally, it

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45 In fact, from the initial MNL specifications reported in Appendix A, it was found that individuals in employment had a (slightly) positive charging duration coefficient. The corresponding interaction terms were not preserved in the final specification of Table 17 because it is common practice in specification searches to exclude statistically significant terms with counterintuitive signs, if these are not "highly relevant or policy variables" (Ortuzar and Willumsen, 2011).

46 In fact, from initial the MNL specifications reported in Appendix A, it was found that individual in employment and planning to travel to work had a (slightly) positive charging duration coefficient. The

could be the result of a preference for just in time charging or the result of the a positive attitude towards the smart charging operation, viewed as beneficial to society. From this perspective, one may prefer to have one's EV involved in the charging operation for most or all the time that the vehicle is parked.

A positive covariance between available energy and charging duration coefficients means that individuals choosing higher charging durations tend to also choose higher available energy levels. It would be expected that individuals accepting longer charging durations may do so if a high level of available energy can be obtained.

<u>*A few caveats*</u>

In general, the significant interaction terms with socio-demographics and available energy and charging duration should be considered as the result of exploratory analyses which need confirmation by collecting further data and estimating the models on larger samples. Moreover, additional attitudinal data on attitudes to risk and ambiguity should be collected to test whether the effect of demographics may instead be the result of correlated attitudes to ambiguity. The use of integrated choice and latent variable (and latent class) models belonging to the general class of hybrid choice models could indeed make these links between individuals' attitudes, socio-demographics and charging operation attributes more explicit.

IMPLIED WILLINGNESS TO PAY (MNL)

Table 18: Trade-off ratios, choice experiemnt1 (MNL)

		MIN	**MAX**
Willingness to pay for E	£/kWh	0.05	2.13
Value of CT (*)	£/h	0.027	0.086
(*)Only based on the significant terms in Table 17			

The ratio between the marginal utility for available energy and the marginal utility of the income (i.e. the cost coefficient) can be interpreted as the marginal willingness to pay for available energy. The ratio between the marginal utility of charging duration and the cost coefficient can be interpreted as the marginal willingness to pay for a reduction in charging

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corresponding interaction terms were not preserved in the final specification of Table 17, because it is common practice in specification search to exclude statistically significant terms with counterintuitive signs, if these are not "highly relevant or policy variables" (Ortuzar and Willumsen, 2011).

duration, or the monetary value of charging time (VCT): it represents a monetary value for reducing the time during which the vehicle is not operational due to charging requirements. These two monetary valuations as implied by the MNL model estimates in Table 17 are shown in Table 18.

The WTP for E varies from a minimum of 5p per kilowatt-hour to a maximum of £2.13 per kilowatt-hour and the VCT between 3p and 9p per charging hour. The upper extreme of the WTP range significantly exceeds average domestic electricity unitary costs in 2012 (the year the survey was carried out), which amount to 15p per kWh. The corresponding willingness to pay for range, if one considers a fuel consumption of 0.32 kWh per mile (halfway between the fuel consumption for maximum range and the fuel consumption for minimum range as hypothesised in the ECarSim survey) varies between less than 0.016£/mile and 0.68 £/mile Note that the fuel cost per mile of a 2012 Ford Focus is 0.131 £/mile[47].

5.4 A latent variable approach to accommodating the effect of range anxiety in charging choices

Nilsson (2011), reviews the popular and scientific press on electric vehicles and consumer behaviour and finds that the most frequent definition of range anxiety is fear (or concern) of not reaching a destination when driving an EV. In the EV literature, however, nuances are found regarding the nature of this concern. For example, (Tate et al., 2009) describe it as a "continual fear or concern", but it has also been interpreted as context-linked and situation specific. For example, (Botsford and Szczepanek, 2009) use range anxiety to explain the fact that, in a trial carried out by Tokyo Electric Power Company in 2007, the introduction of a fast charger (in addition to the already available slow chargers), increased the geographical area covered by participating electric vehicle drivers, without a significant increase in usage rates for the new charger.

A way to view the effect of range anxiety on EV use (and indeed charging) choices, could be as the effect of risk attitudes in choices under uncertainty. An individual fears not being able to reach their destination if they consider that the available range is uncertain. Indeed, because the range achieved depends on variables such as driving style, use of heating or cooling, vehicle load and road gradient, choosing which battery level to depart with entails inherent

[47] For example the fuel cost for a Ford Focus 1.6 Duratec Ti-VCT (85PS) 5 Door, is rated £ 1,572 for 12,000 miles, (VCA, 2013). This gives a cost per mile of 13.1p/mile.

uncertainty. Experienced users may be able to predict the range over a set of familiar journeys, but they may face uncertainty occasionally when they decide to use their electric car for unfamiliar journeys or driving conditions. Individuals' risk attitudes will affect EV use (and charging) choices, which therefore could be modelled as choices under uncertainty. This approach was adopted by the author and colleagues to study charging choices on the same dataset used for the analysis of the present section (Daina et al., 2013). An alternative approach is to view range anxiety a latent characteristic of the individual EV driver that can be more or less affected by the concern of remaining stranded, despite the actual risk. The advantage of this approach with respect to the traditional approaches in modelling choice under uncertainty is that no assumptions regarding the subjective distribution of the uncertain quantity has to be made.

In this section, this second perspective is taken. An ICLV approach is used to explore the effect of 'range anxiety' as a latent construct that may affect charging choices. In the context of SCE1, because only home charging is available, the range concern is likely to be associated with both reaching the out of home destination and getting back home, i.e. of not completing the tour. The ICLV model is estimated using the subsample of observations from choice SCE1 whose choice set contains at least one alternative characterised by ambiguity in tour feasibility. Thus, in all choice situations there is at least one alternative which implies a risk of not completing the planned tour, meaning that all choice situations contain alternatives potentially causing range anxiety.

Besides considering range anxiety as a concern regarding not reaching the destination, we also hypothesise that some individuals would generally tend to be more or less affected by range anxiety than others, regardless of the specific choice situation and that indicators may exist which could capture this individual latent individual characteristic.

Because it is latent, range anxiety cannot be directly measured. It can, however, be hypothesised that individuals more prone to range anxiety tend to adopt a more precautionary approach when appraising an available energy level than the average population. We therefore propose that range anxiety will have the effect of increasing the marginal utility for available energy when making charging choices. Moreover, if other indicators of the underlying range anxiety are available, the modelling framework represented in Figure 21 could be considered. The latent variable range anxiety modelled as a function of the characteristics of individuals may inform both the charging choices and the latent variable measurement indicator.

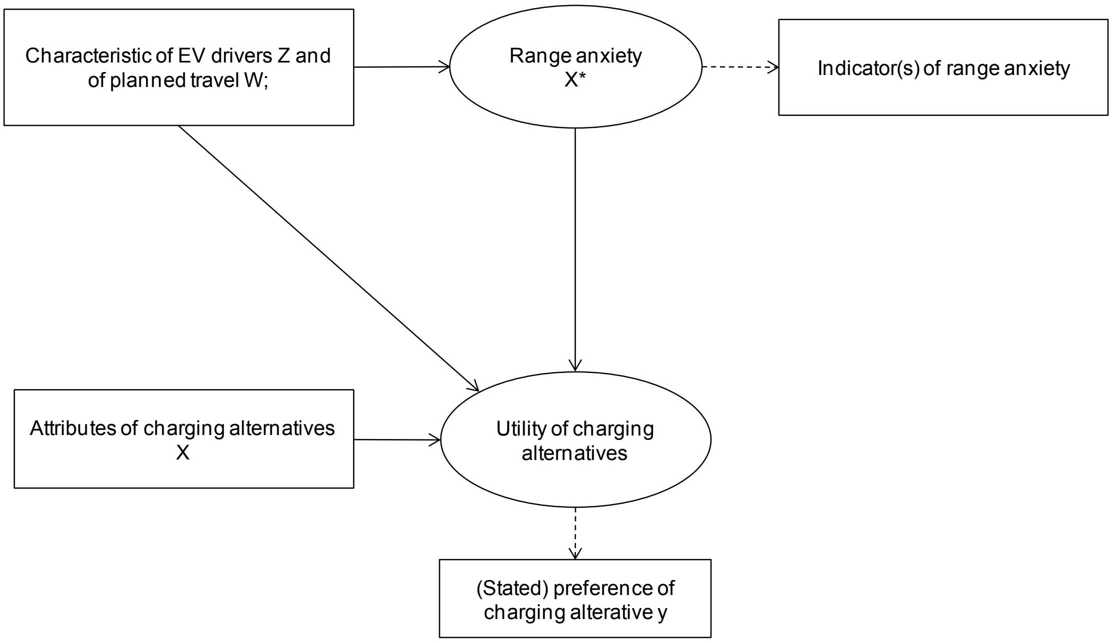

Figure 21: ICLV modelling framework for accommodating the effect of range anxiety on charging choices

In the ECarSim tool the following question was asked: "*Suppose that on a full battery you usually get between 60 and 100 miles before it runs out. How far would you expect to be able to drive after the next full charge?"* Respondents could choose within a range between 0 and 100 miles. It can be assumed that people who are more concerned about not having enough range would adopt a more conservative (risk averse) approach to range appraisal, and would therefore tend to have lower range expectations than others. We could, therefore, consider the inverse of the answer to such a question as an indicator of the unobservable variable called 'range anxiety'. In the EcarSim sample the answers to the question above are distributed as in Figure 22. Let us call the answer to this question the stated full charge expected range (FCER). We define this as the range anxiety indicator, the inverse of FCER, i.e.:

$$I_{RA_n} = 1/FCER_n \tag{5.23}$$

I_{RA_n} is expected to increase as range anxiety increases because individuals who are more concerned with not having enough range for their needs will tend to indicate lower FCER values when asked.

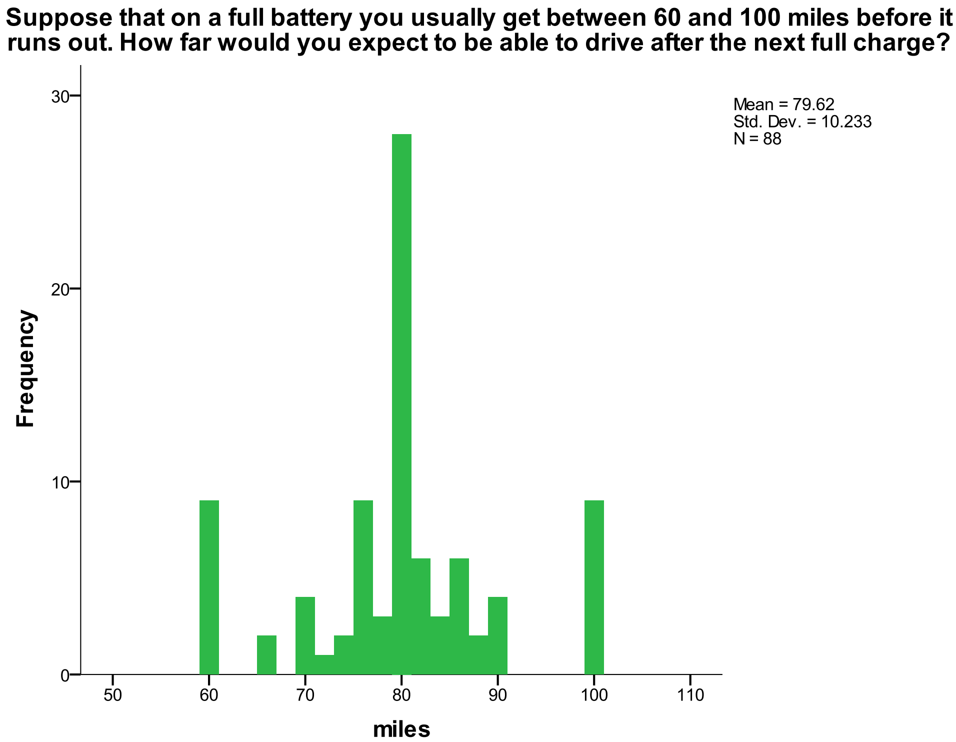

Figure 22: Distribution of FCER in the ECarSimSample

5.4.1 Model structure

The structural and measurement equations defining the hybrid charging choice model that accommodates the latent range anxiety are defined as follows:

Latent variable structural model

Let scalar variable X_n^* represent the latent variable range anxiety. Let us assume this is a linear function of individual characteristics only:

$$X_n^* = \gamma Z_n + \omega_n, \qquad \omega_n \sim N(0, \sigma_\omega^2) \tag{5.24}$$

where Z_n is a vector of the characteristics of individual n (i.e. socio-demographics) and ω_n is a zero mean normally distributed random term with variance σ_ω^2. Note that in the present specification, for the sake of model parsimony, only demographics are included as explanatory variables in the structural model whereas, in fact, tour travel pattern characteristics could also be used. Indeed, as long as the latent variable has a significant impact on both the choice model and the measurement model, this is enough to confirm that range anxiety plays a role in choice behaviour (given the assumption that the range anxiety indicator chosen is appropriate). In particular, the latent variable structural equation was specified in terms of age, gender and employment status.[48]

Latent charging utility structural model

The relationship between choice attributes and the latent utilities defines structural relationship of the choice model:

$$U_{ns} = V_{ns} + \nu_{ns} = X_{ns}F_1\beta + X_n^* I X_{ns}F_2\beta + \nu_{ns} \tag{5.25}$$

where

$U_{ns} = \begin{Bmatrix} U_{ns1} \\ U_{ns2} \end{Bmatrix}$ is the vector of utilities for the two alternatives in choice experiment 1;

ν_{ns} is a vector of IID extreme value type I error terms

$V_{ns} = \begin{Bmatrix} V_{ns1} \\ V_{ns1} \end{Bmatrix} = U_{ns} - \nu_{ns}$;

$X_{ns} = \begin{bmatrix} E_{ns1} & CT_{ns1} & CC_{ns1} \\ E_{ns2} & CT_{ns2} & CC_{ns2} \end{bmatrix}$ is the matrix of charging attributes;

$\beta = \begin{Bmatrix} \beta_E \\ \beta_{CT} \\ \beta_{CC} \\ \beta_{X^*E} \end{Bmatrix}$ is a vector of utility coefficients;

F_1, F_2 and I are matrices used to express in vector from the relationship with the vector β of the utility coefficients and, observed attributes X_{ns} and the latent variable X_n^*:

$F_1 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$, $F_2 = \begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$ and I is a (2x2) identity matrix.

The utility expression so defined assumes that the latent variable range anxiety has an effect on the marginal utility of available energy, as intuition would suggest.

[48] Other individual characteristics were tested, but their effect was not found to be significant.

Measurement equation for latent variable

The latent variable measurement model provides the relationship between that latent variable range anxiety and the range anxiety indicator. A linear specification is adopted here:

$$I_{RA_n} = \theta_0 + \theta X_n^* + \epsilon_n, \qquad \epsilon_n \sim N(0, \sigma_\epsilon^2) \tag{5.26}$$

Here, θ_0 is a constant, θ is a coefficient that determines the impact of the latent variable on the value of the indicator and ϵ_n is a random error term. In ordered to avoid the estimation of θ_0, the indicator can be centred about its mean. According to what is customary in the literature, the random ϵ_n component is assumed to be normally distributed with variance σ_ϵ^2 (Bolduc and Daziano, 2008).

Measurement equation for choice model

Consider a binary indicator y_{ns} that takes value 1 when alternative A is chosen in choice experiments 1 and 2 when alternative B is chosen. The measurement equation for the choice model is therefore:

$$y_{nsj} = \begin{cases} 1 & U_{nsj} \geq U_{nsi}, j \in \{1,2\}, j \neq i \\ 0 & otherwise \end{cases} \tag{5.27}$$

Each respondent in choice experiment 1 faces a different number S_n of uncertain choice situations, depending on their travel distance. The probability of the sequence of choices$I_n = \{i_1, \dots I_{S_n}\}$, conditional on X_n^* is:

$$\Pr(I_n | X_n, \beta, X_n^*) = \prod_{s=1}^{S_n} L_{ni_s} \tag{5.28}$$

where $L_{ni_s} = \frac{\exp(V_{nsi_s}(X_{nsi_s}, X_n^*, \beta))}{\sum_{j=1}^{2} \exp(V_{nsj}(X_{nsj}, X_n^*, \beta))}$ is the probability of choosing alternative i_s in choice situation s conditional on the latent variable X_n^*. The unconditional choice probability for the sequence of choices I_n is then given by:

$$P_{I_n} = \Pr(I_n | X_n, \beta, \gamma, \sigma_\omega) = \int_{X^*} \prod_{s=1}^{S_n} L_{ni_s} f(X_n^* | Z_n, \gamma, \sigma_\omega) dX_n^* \tag{5.29}$$

5.4.2 Estimation

The integrated choice latent variables model above was estimated using Maximum Simulated Likelihood estimation. A Matlab code was written for the purpose of simultaneously estimating the latent variable and choice models.

The log-likelihood function to be maximised is:

$$LL = \sum_{n=1}^{N} \ln\left[\int_{X^*} g\left(I_{RA_n}\middle|X_n^*, \theta_0, \theta, \sigma_\epsilon\right) \prod_{s=1}^{S_n} \widetilde{L_{ns}}\, f(X_n^*|Z_n, \gamma, \sigma_\omega) dX_n^*\right] \quad (5.30)$$

where $g\left(I_{RA_n}\middle|X_n^*, \theta_0, \theta, \sigma_\epsilon\right)$ is the density of I_{RA_n}. Because in the measurement model the error term ϵ_n is assumed to be normally distributed, then $g\left(I_{RA_n}\middle|X_n^*, \theta_0, \theta, \sigma_\epsilon\right) = \frac{1}{\sigma_\epsilon}\phi\left(\frac{I_{RA_n}-\theta_0+\theta X_n^*}{\sigma_\epsilon}\right)$. Moreover, $\widetilde{L_{ns}}(\dots, X_n^*)$ is the logit formula evaluated for the chosen alternative in choice situation s.

Substituting the expression of X_n^*, and considering that $\omega_n = \sigma_\omega \xi_n$, $\xi_n \sim N(0,1)$, then the integral over the density of X_n^*, becomes an integral over a standard normal distribution. The expression of the log-likelihood function becomes

$$LL(\beta, \gamma, \sigma_\omega, \theta_0, \theta, \sigma_\epsilon) = \sum_{n=1}^{N} \ln \int_{-\infty}^{+\infty} \frac{1}{\sigma_\epsilon}\phi\left(\frac{I_{RA_n} - \theta_0 + \theta(Z_n\gamma + \sigma_\omega \xi)}{\sigma_\epsilon}\right) \prod_{s=1}^{S_n} \widetilde{L_{ns}}\, \phi(\xi) d\xi \quad (5.31)$$

5.4.3 Model identification and normalisation

In the present model the Bolduc-normalisation strategy is adopted so that the sign of the impact of the range anxiety on the indicator can be verified. In order to empirically verify that the model is identified, several of the empirical identification tests suggested by (Walker, 2001) were undertaken:

- The Hessian matrix of the log-likelihood function is non singular.
- The parameters are also stable as the number of draws utilised in maximum simulated likelihood estimation increases. Figure 23 shows parameter estimates for different number of draws and different starting points. Note that all estimates for all model

runs are well within one standard error. Parameter estimate values and model statistics for each model run are available in Appendix B.

- Parameters obtained from model runs with different starting points converge in the maximum simulated likelihood estimation to the same likelihood parameter values (see Figure 23 and Appendix B)
- Monte Carlo experiments are conducted to generate synthetic data using the specified model structure and the estimated parameters. Next, the synthetic data are used to re-estimate the model. Figure 24 shows the parameter estimates from several synthetic datasets, together with the original model parameters. The parameters estimates from the synthetic datasets of the same size as the original dataset (755 observations, 88respondents) float around the original model parameters. Increasing the synthetic dataset size lead to more accuracy in the retrieval of the original parameters (Figure 25). Indeed in this latter case (only) t-tests on parameters obtained using the synthetic dataset do not reject the hypothesis of equality with the original parameters. Parameter estimates values and model statistics for each model run are available in appendix B.

The outcomes of the tests described above indicate that the model is identified.

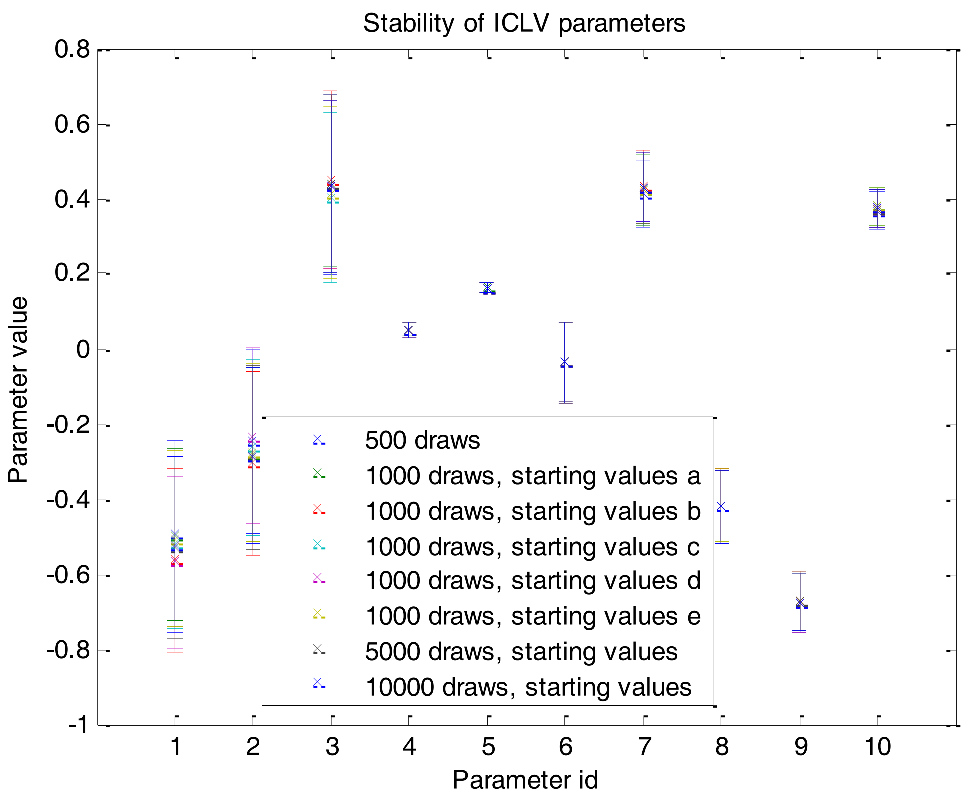

Figure 23 Stability of range anxiety ICLV model parameters, at different starting point and number of random draws (500, 1000 estimations, 5000, 10000).

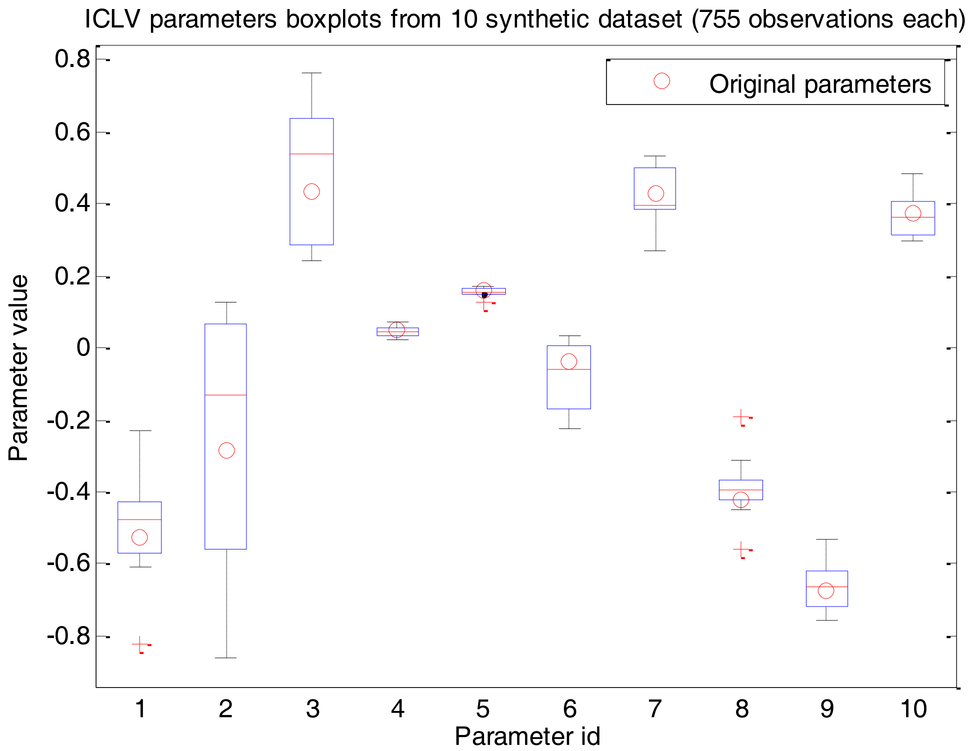

Figure 24: Retrieval of model parameters from simulated data 755 observation

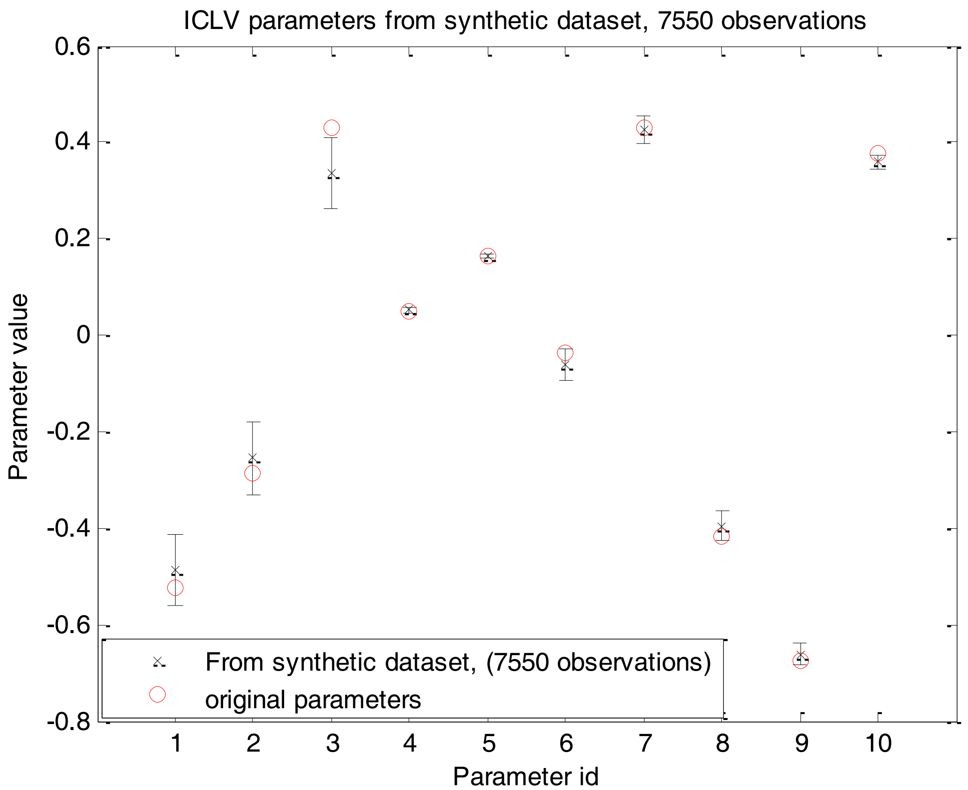

Figure 25: Retrieval of model parameters from synthetic data 7550 observations (880 individuals)

5.4.4 Model results

Table 19 shows the maximum simulated likelihood estimates of the ICLV model structure described above. Amongst the structural model parameters only age is significant at the 95% confidence level. The effect of employment has 10% significance, while the effect of gender is not significant.

The signs of the latent variable structural parameters show that the young age group tends to exhibit lower range anxiety; this may reflect a lower risk aversion amongst the members of the younger age group. The effect of gender is negative (but not significant). On the contrary, the effect fulltime employment is positive, i.e. represents a higher concern for range

The positive sign of the impact on the measurement model indicates that the latent variable is positively correlated with the inverse of FCER. This allows us to interpret the latent variable as capturing an increasing cautiousness in the appraisal of the expected range availability given a certain battery level. The positive sign of the parameter β_{X^*E} shows that what we termed range anxiety contributes to increasing the marginal utility for available energy, according to what was hypothesised.

Table 19 ICLV model to account for range anxiety, choice experiment 1 data

	parameter	id	value	st-err	t-stat	value	st-err	t-stat
Structural model	$\gamma_{Age\ 36+}$	1	-0.496	0.228	-2.172	***	***	***
Structural model	γ_{Female}	2	-0.281	0.231	-1.217	***	***	***
Structural model	$\gamma_{Employed(full\ time)}$	3	0.441	0.222	1.982	***	***	***
Structural model variance st. dev.	σ_{ω}	***	1.000	fixed	***	***	***	***
Measurement model	θ	4	0.050	0.020	2.507	***	***	***
Measurement model	σ_{ϵ}	5	0.163	0.013	12.760	***	***	***
Choice model	A	***	0.000	fixed	***	0	fixed	***
Choice model	B	6	-0.037	0.106	-0.345	-0.043	0.082	-0.521
Choice model	β_E	7	0.425	0.094	4.534	0.181	0.019	9.421
Choice model	β_{CT}	8	-0.421	0.097	-4.333	-0.364	0.071	-5.133
Choice model	β_{CC}	9	-0.674	0.078	-8.617	-0.334	0.050	-6.632
Choice model	β_{X^*E}	10	0.381	0.051	7.519	***	***	***
N of draws	1000							
N of parameters	9					4		
N of respondents	88					88		
N of observations	755					755		
Overall model log-likelihood	-337.128					***		
Choice model null log-likelihood	-523.326					-523.326		
Choice model final log-likelihood	-370.501					-464.394		
Choice model adjusted rho	0.273					0.105		
(*) Distance in 100 miles, E in kWh, CT in 10 hours and CC in £								

5.5 Analyses of choice experiment 2

In this section we analyse charging choice behaviour in the presence of alternatives characterised by charging durations that cause delays to a driver's schedule. The rationale underlying this study is that EV drivers may trade available energy (i.e. range) against schedule delays and charging costs. It is generally true that at current charging powers (~3kW-7KW, when dedicated charging points are available), an overnight charge is sufficient to completely recharge most electric car batteries. However, if we explore beyond the conventional scenarios of constant electricity price throughout the day or simple two tier time of day prices, and start considering smart charging scenarios, respondents may face choices in which the charging operation is completed in a much longer time, but the longer charging duration is compensated for with lower electricity prices.

While in choice experiment 1 the charging duration would not affect the timing of the (planned) journey, in smart charging scenarios we may consider situations in which a charging service provider could incentivise postponing the end of the charging operation to a time beyond the electric vehicle driver's preferred departure time. The driver may (a) decide to accept the offer, and delay the departure; (b) charge to a lower battery level and maintain the departure at the preferred time so that only a certain amount of battery is charged at higher prices; or (c) simply pay more to obtain his or her preferred battery level and not incur schedule delays.

5.5.1 Choice experiment 2 description and base utility specification

SCE2 presents respondents with two charging options before the same return journey by electric car, as in SCE1. However it differs from choice experiment 1 in two ways, as Figure 26 shows. Firstly, the charging operation lasts either for the whole dwell time at home of the vehicle, or longer, thus introducing in the latter case a schedule delay (late). Secondly, it allows a flexible response to the respondent with respect to the use of the EV for the tour, in the following terms:

- Respondent always have available the alternatives:
    - Avoid both charging strategies and do not travel;
    - Avoid both charging strategies and travel with other mode.
- For those charging alternatives inducing a schedule delay, respondents are provided with options to partially absorb the schedule delay by curtailing the duration of the activity at the destination, choosing from a menu of activity participation levels (characterised by different levels of reduction in activity duration) including zero participation decreases (i.e. maintaining the original activity duration).

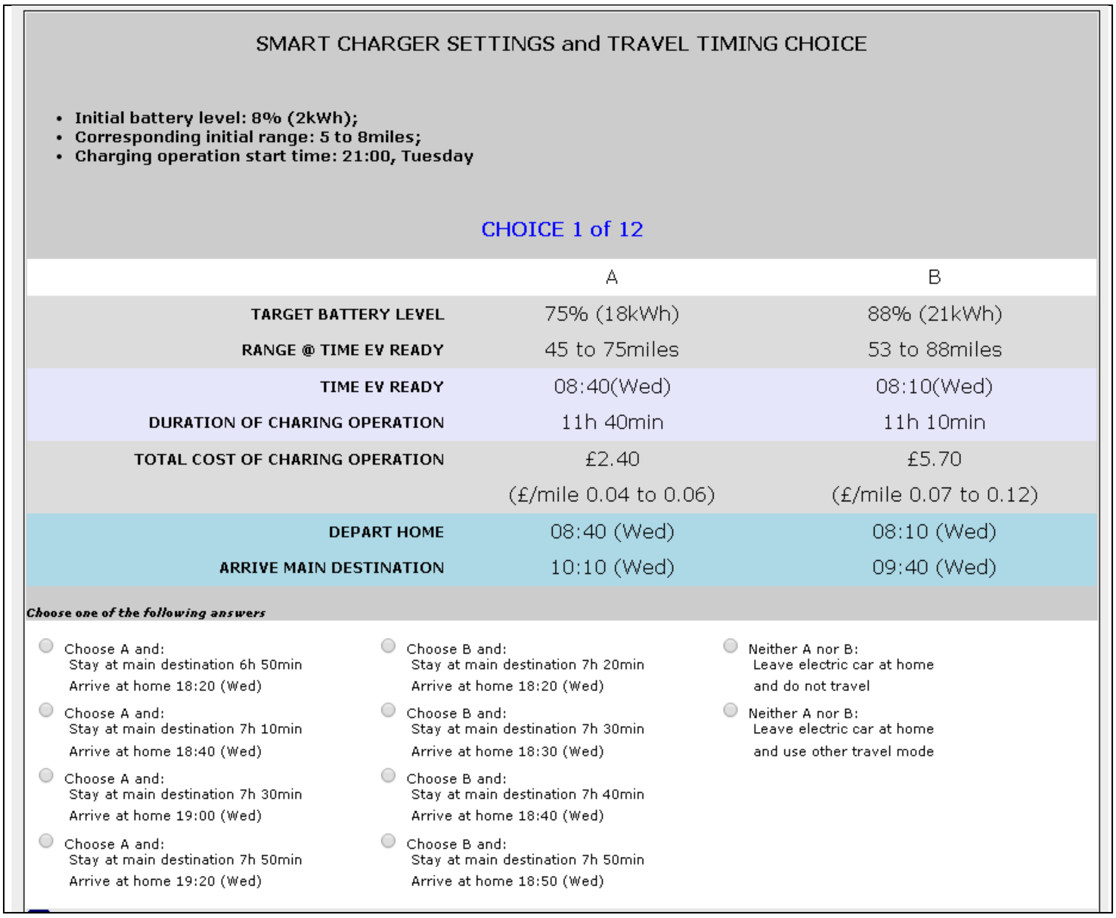

Figure 26: An example of a choice task from choice experiment 2 of ECarSim

The utility for the alternatives entailing charging and using the electric vehicle for the tour are specified as:

$$U_{nsi} = \\ = \beta_E EV + \beta_E E_{nsi} + \beta_{SDL} CISDL_{si} + \beta_{DL} DL_{si} + \beta_{CC} CC_{nsi} \\ + \beta_{PD} PD_{nsi} + \epsilon_{nsi} \tag{5.32}$$

These alternatives are at most eight, because there are two charging strategies and, for each of these, at most four curtailing options for the activity at destination, when the charging duration entails a schedule delay. In the expression above,

- EV is a dummy variable equal to one for the electric vehicle charging and use alternatives, as opposed to the 'neither A nor B' alternatives.
- E is the available energy in the battery after charging;

- $CISDL$ is charging-induced schedule delay late (caused by the charging operation terminating after the original dwell time at home, therefore causing a delay with respect to the preferred departure time);
- DL is a dummy variable equal to 1 when the schedule delay late is greater than zero;
- CC is the charging cost;
- PD is the activity participation decrease at destination;
- ϵ an error term.
- subscripts n, s and i indicate respectively: individual, choice situation, and alternative.

The systematic utility for the alternative “avoid both charging strategies and do not travel”, is specified by an alternative specific constant (NT, as in no travel) and the activity participation time decrease at destination. In this case PD is equal to the observed activity participation time at destination T_D^* (that is assumed to be the preferred activity participation time).

$$V_{NT=}\beta_{NT}NT + \beta_{PD}T_D^* \tag{5.33}$$

The utility for the alternative “avoid both charging strategies and use other mode” is specified solely by an alternative specific constant other mode (OM), as the mode was not specified in the choice experiment.

$$V_{OM} = \beta_{OM}OM \tag{5.34}$$

5.5.2 Basic specification estimates

We provide below in Table 20 estimates for the base specification in equations (5.32) to (5.34). In the estimation of the model above in addition to the dummy variables indicating the charging and EV use alternatives and the two no charging alternatives (no travel and other mode), we include alternative specific constants for the options to curtail the activity participation time at destination, for charging options A and B, these are, respectively:

- A1, A2, A3 and A4; and
- B1, B2, B3, and B4.

These are numbered base on the position of appearance in the choice task, which also corresponds to the level of activity decrease, maximum at A1 (B1) and zero at at A4 (B4).

The MNL estimates obtained for the base specification terms are all significant and have intuitive signs.

- The coefficients for charging cost, schedule delay late, and decrease in activity participation time at destination and delay late dummy are negative;
- Available energy after charging has a positive coefficient.
- The EV dummy has a positive coefficient and OM as well (NT is used as base category and its coefficient fixed to zero for identification).

β_{EV} is larger than β_{OM} showin that in the ECarSim sample the alternatives entailing EV use are preferred over shifting to another mode or avoid travelling.

The values alternative specific constants for option at destinations show that respondents tend to choose either the maximum curtail option or zero curtail.

Table 20 Charging choice model – choice experiment 2 data, base MNL specification

Variable in model (*)	Coefficient	Std err	t-test
A1	-0.182	0.16	-1.14
A2	-1.15	0.223	-5.13
A3	-1.23	0.23	-5.34
A4	-0.0054	0.115	-0.05
B1	-0.04	0.159	-0.25
B2	-1.24	0.237	-5.22
B3	-1.5	0.262	-5.7
B4	0	fixed	
NT (no charging and no travel)	0	fixed	
EV(charge and use EV)	2.17	0.374	5.79
OM (no charging and travel with other mode)	1.23	0.289	4.26
PD, [h]	-0.131	0.0521	-2.52
CC, [£]	-0.175	0.0288	-6.07
E, [kWh]	0.073	0.0134	5.45
CISDL, [h]	-0.786	0.135	-5.81
DL	-1.87	0.198	-9.44
Number of observations:	1056		
Null log-likelihood:	-2207.2		
Final log-likelihood:	-1526.6		
Likelihood ratio index, ρ	0.308		
Adjusted likelihood ratio index, ρ_{adj}	0.302		

(*) Appendix D provides reference tables with the definitions of the variables

The marginal WTP for available energy is ~0.42£/kWh. This value is in line with the WTP implied in SCE1 1 0.41£/kWh (Table 16, restricted model).

The ratio between the schedule delay late coefficient to the cost coefficient and activity time coefficient to cost provides a monetary value of time estimates. The values of times implied by the schedule delays and activity participation time decrease are ~4.49£/hour, ~0.75£/hour respectively. These values appear to be in line with values found in the literature. For reference we report in Table 21 the values obtained from estimates of a time of day choice model (an error component logit) estimated by (Hess et al., 2007) on stated preference data, collected in 2004 in the West Midlands of the United Kingdom, to inform the PRISM model (RAND Europe, 2004). Clearly the comparison with the West Midlands data should only be considered as indicative, given that the bulk of the ECarSim sample is London based, moreover the West Midlands data is 10 years old. It should be noted that a London dataset also exists from which a corresponding monetary valuation of schedule delay and activity participation decrease can be obtained. This was collected for the APRIL model (see Polak and Jones 1994) but it is even older than the West Midlands dataset. For comparison, therefore we show here only the values obtained from the West Midlands data for schedule delay late and the activity participation time decrease at the destination.

Table 21: Values of times implied by schedule delay late and activity participation time decrease obtained by 2004 West Midlands time of day choice experiments

	Commute flexible	Commute fixed	Business	Other
β_C, cost in p (*)	-0.01009	-0.0073	-0.0051	-0.0121
β_{SDL}, CISDL in minutes (*)	-0.0285	-0.1059	-0.0197	-0.0374
β_{PD}, PD in minutes (*)	-0.00329	-0.0025	-0.006	***
β_{SDL}/β_C £/hours	1.69	8.70	2.32	1.85
β_{PD}/β_C £/hours	0.20	0.21	0.71	***

(*) Source: (Hess et al., 2007)

5.5.3 Systematic taste variations

To the base specification, the specification shown in Table 22 includes interaction terms with observed individual characteristics and original tour characteristics, in order to capture systematic variations in the marginal utilities for charging and schedule attributes. Note that, for model parsimony, interaction terms are specified only with the three design variables of SCE2 (available energy, schedule delay late, and charging cost) and the EV dummy, while the variable PD is not interacted with any individual or tour characteristic. We summarise below the effect of the interaction terms. Concerning available energy and cost, the same interaction terms that were found to be significant in SCE1 are included in this specification for SCE2. On this occasion, however, given the qualitative difference of charging induced schedule delay, compared to a charging duration that does not induce travel pattern disruptions, a wider set of interaction terms are included to explore systematic heterogeneity. The variables included in these interaction terms are the same as those summarised in Table 11, with the addition of a dummy variable that specifies whether a respondent has stated that the timing of the tour is in fact not flexible[49].

[49] In particular the indicator corresponds to providing the answer "strongly disagree" to a question asking whether the respondent agreed with the statement "The timings of my travel and activity (-ies) of this tour are fairly flexible", in which the level of agreement was gauged using a 5 level Likert scale: "strongly disagree", "somewhat disagree", "nether agree nor disagree", "somewhat agree", and "strongly agree". It is acknowledged that direct use of indicators in the utility specifications may induce endogeneity and measurement errors (Hess, 2011), which could be prevented by specifying a hybrid choice model in which tour timing flexibility is modelled as a latent variable measured by means of the indicator. For the sake of simplicity, however, at this stage it was decided to use a direct indicator in the model specification.

Table 22: Charging choice model – SCE2 data, MNL specification for systematic heterogeneity in tastes for charging operation attributes'.

Variables in models(*)	Coefficient	Std err	t-test
A1	-0.169	0.164	-1.03
A2	-1.16	0.226	-5.12
A3	-1.26	0.233	-5.41
A4	-0.0259	0.12	-0.21
B1	0.0184	0.16	0.11
B2	-1.2	0.238	-5.04
B3	-1.48	0.263	-5.62
B4	0	fixed	
NT (no charging and no travel)	0	fixed	
OM (no charging and travel with other mode)	0.885	0.299	2.96
EV	6.62	0.902	7.34
EV*Education tour purpose	-0.896	0.63	-1.42
EV*Leisure/Social tour purpose	0.463	0.601	0.77
EV*Work tour purpose	-0.74	0.343	-2.15
EV*Distance 41-50 miles	-2.32	0.755	-3.07
EV*Distance 51-60 miles	-6.14	1.06	-5.76
EV*Distance 61+ miles	-5.92	1.9	-3.12
EV*Employed	-2.47	0.609	-4.05
EV*Female	-1.35	0.527	-2.55
EV*Age 20-35	-0.447	0.467	-0.96
EV*Age 36-55	-0.819	0.42	-1.95
EV*No university	-0.54	0.25	-2.16
CC, [£]	-0.302	0.0905	-3.34
CC*Employed, [£]	0.119	0.0889	1.34
CC*Age 20-35, [£]	-0.105	0.0546	-1.92
E, [kWh]	0.054	0.0217	2.48
E*Female, [kWh]	0.0283	0.0262	1.08
E*Leisure/Social tour purpose, [kWh]	-0.0217	0.0254	-0.86
E*Distance 41-50 miles, [kWh]	0.134	0.0362	3.71
E*Distance 51-60 miles, [kWh]	0.246	0.0499	4.94
E*Distance 61+ miles, [kWh]	0.25	0.0855	2.92
CISDL	-1.32	0.434	-3.03
CISDL*Education tour purpose, [h]	-0.366	0.951	-0.38
CISDL*No university, [h]	0.197	0.206	0.96
CISDL*Work tour purpose, [h]	0.649	0.296	2.19
CISDL*Employed, [h]	1.1	0.359	3.06
CISDL*Female, [h]	-0.0912	0.173	-0.53
CISDL*Leisure/Social tour purpose, [h]	0.38	0.261	1.46
CISDL*Age 20-35, [h]	-0.668	0.265	-2.52
CISDL*Age 36-55, [h]	-1.21	0.284	-4.28
CISDL*Travel in peak periods, [h]	-1.05	0.23	-4.55
CISDL*Timing of travel not flexible, [h]	-2.37	0.308	-7.69
DL	-1.53	0.231	-6.61
PD, [h]	-0.189	0.0525	-3.59
Number of estimated parameters	42		
Number of observations	1056		
Null log-likelihood	-2207.22		
Final log-likelihood	-1349.1		
Likelihood ratio index, ρ	0.389		
Adjusted likelihood ratio index, ρ_{adj}	0.37		

(*) Appendix D provides reference tables with the definitions of the variables

Interactions with the EV dummy

- Individuals in employment and women are less likely than the rest of the sample to choose the EV charging use options; the same applies for individuals in the mid age group (36-55 years old); the same applies for individuals without a university degree.
- Individuals planning to drive distances above 50 miles are less likely than the others to choose the EV charging and use options;
- Individuals planning to travel to work or to school (education tour purpose) are less likely to choose the EV charging and use options.

These results show that these groups of individuals tend to respond to disruption to travel patterns induced by charging, or to too low available energy levels, by avoiding the use of EVs.

Interactions with charging cost

- Age has the same effect as in SCE1, increasing the cost sensitivity for the young (recall that age is correlated with income);
- Employment has the same (positive) effects as in SCE1, but its effect is not really significant.

Interactions with available energy

- Tour distance increases the marginal utility for available energy. This confirms what was found in choice experiment 1 (at least in the high distance subsample or the subsample with ambiguity in tour feasibility).
- The gender effect here is not significant. In this choice situation, which does not enforce to trade energy with cost (or schedule delay) women, instead of trading energy and cost levels, when facing undesirable charging and EV use alternatives tend to choose the escape alternatives.

Interactions with schedule delay late

- The youngest and the mid age group attain a stronger disutility for schedule delay than the base level (the older age group, 61+ years old), with the mid age group showing the strongest disutility. Indeed, it is reasonable to think that individuals in the midst of their productive life have higher value of time.
- Gender does not appear to have a significant effect.

- Education level does not have a significant effect, as opposed to the charging duration case in in the MNL specification for SCE1.
- Individuals in employment appear to have a lower sensitivity for schedule delay than others. This observation is difficult to explain and indeed may appear counterintuitive, since individuals in employment could be expected to show a higher value of time. This phenomenon is also found in SCE1, with respect to charging duration, however, and although it is not made explicit in the specification of Table 17, it can be observed from the model specification for SCE1 shown in Appendix A (see also footnote 45).
- For leisure and social tours, a lower disutility for schedule delay is observed, with respect to the base level (other tour purpose). Somewhat against intuition such disutility is even lower for work tours (the corresponding parameter is also significant at the 5% level. This phenomenon is also found in SCE1, with respect to charging duration, however, and although it is not made explicit in the specification of Table 17, it can be observed from the model specification for SCE1 shown in Appendix A (see also footnote 46).
- Tour timing flexibility has a strong and highly significant effect, with inflexible tour timings increasing the magnitude of the schedule delay parameter. This result is coherent with what is found in the travel time choice literature (see Table 21) and quite intuitive: if the tour times are (perceived as) inflexible than the disutility for schedule delay is higher.
- If the travel is planned to take place in a period likely to be characterised by congestion, a schedule delay late is valued even more negatively. This is coherent with the effect of peak time travel in charging duration found in SC1. It was suggested that the preference for shorter charging times could reflect a preference for greater departure time flexibility, to hedge against low travel time reliability at times of road congestion.

5.5.4 Random taste heterogeneity

Table 23 presents the estimates of the random coefficients mixed logit model. The coefficients that are specified as random are the available energy coefficient (β_{E_n}) and the schedule delay coefficient (β_{SDL_n}). As in the case of SCE1, this model is intended to gauge the residual variability in the tastes for those two attributes, in a specification in which systematic heterogeneity is partially being captured using interaction terms. As in SCE1, and for the same reasons, the two random coefficients are specified as normally distributed. In the present case, we also estimated the covariance between the two, i.e. we assume:

$$\begin{Bmatrix} \beta_{SDL_n} \\ \beta_{E_n} \end{Bmatrix} \sim N\left(\begin{Bmatrix} \beta_{SDL} \\ \beta_E \end{Bmatrix}, \begin{bmatrix} \sigma_{SDL}^2 & \sigma_{E,SDL} \\ \sigma_{E,SDL} & \sigma_E^2 \end{bmatrix} = \begin{bmatrix} \lambda_1 & 0 \\ \lambda_3 & \lambda_2 \end{bmatrix} \begin{bmatrix} \lambda_1 & 0 \\ \lambda_3 & \lambda_2 \end{bmatrix}^T\right) \tag{5.35}$$

where $\Lambda = \begin{bmatrix} \lambda_1 & 0 \\ \lambda_3 & \lambda_2 \end{bmatrix}$ is the Cholesky matrix of the random coefficients covariance matrix.

We note here that the specification of the systematic heterogeneity is slightly different, from that in Table 22 because the parameters that were not significant at least at the 20% level were excluded. Moreover, the two higher distance levels were merged, because the difference coefficients of the respective interaction terms were not found to be statistically different.

The model result shows that all the systematic heterogeneity effects that were observed in the MNL specification estimates are retained also in the mixed logit estimates, although in a few cases, some effects that were significant at the 5% level do not retain this level of significance. Apart from the effect of the work tour purpose on the schedule delay, however, they remain significant at the 10% level.

We avoid replicating here observations regarding the quality of the systematic heterogeneity effects that were pointed out earlier for the MNL estimation.

The fact that the estimated elements of the Cholesky factor of the covariance matrix for the two random coefficients are not all significant (the off-diagonal element is not) leads to an insignificant estimate for the variance estimate of the available energy coefficient, as well as to an insignificant covariance estimate. What remains strongly significant is the variance of the schedule delay coefficient. The estimated standard deviation for the schedule delay coefficient is also large compared to the base mean coefficients (20% larger), indicating that there is a strong residual heterogeneity, despite the significant terms capturing heterogeneity around the mean.

Table 23 Charging choice model – SCE2 data. Mixed logit specification for systematic and unobserved heterogeneity in tastes for charging operation attributes

Variables in model (*)	Coefficient	Std err		t-test
A2	-1.11	0.212		-5.23
A3	-1.21	0.22		-5.51
B2	-1.13	0.225		-5.02
B3	-1.41	0.253		-5.59
NT (no charging and no travel)	0	fixed		
OM (no charging and travel with other mode)	0.781	0.3		2.6
EV	11.8	1.62		7.29
EV*Education tour purpose	-2.98	1.23		-2.42
EV*Leisure/Social tour purpose	0	fixed		
EV*Work tour purpose	-0.81	0.503		-1.61
EV*Distance 41-50 miles	-4.81	1.06		-4.52
EV*Distance 51-60 miles	-10.9	1.51		-7.22
EV*Distance 61+ miles	-10.9	Constrained equal to above		
EV*Employed	-6.04	1.33		-4.53
EV*Female	-1.17	0.513		-2.29
EV*Age 20-35	0	fixed		
EV*Age 36-55	-1.63	0.605		-2.7
EV*No university	-1.31	0.622		-2.11
CC, [£]	-0.604	0.15		-4.03
CC*Employed, [£]	0.288	0.147		1.96
CC*Age 20-35, [£]	-0.247	0.0765		-3.23
E, [kWh]	0.108	0.0276		3.91
E*Female, [kWh]	0	fixed		
E*Leisure/Social tour purpose, [kWh]	0	fixed		
E*Distance 41-50 miles, [kWh]	0.218	0.0595		3.66
E*Distance 51-60 miles, [kWh]	0.446	0.0737		6.05
E*Distance 61+ miles, [kWh]	0.446	Constrained equal to above		
CISDL	-4.33	1.35		-3.2
CISDL*Work tour purpose, [h]	1.53	1.32		1.16
CISDL*Employed, [h]	3.55	1.18		3
CISDL*Leisure/Social tour purpose, [h]	1.45	1.15		1.27
CISDL*Age 20-35, [h]	-3.67	0.953		-3.85
CISDL*Age 36-55, [h]	-5.19	1.14		-4.55
CISDL*Travel in peak periods, [h]	-3.45	1.12		-3.08
CISDL*Timing of travel not flexible, [h]	-8.01	1.27		-6.33
DL	0.554	0.385		1.44
PD, [h]	-0.204	0.0513		-3.97
	Cholesky factor's elements			
$\begin{Bmatrix}\beta_{SDL_n}\\ \beta_{E_n}\end{Bmatrix} \sim N\left(\begin{Bmatrix}\beta_{SDL}\\ \beta_{E}\end{Bmatrix}, \begin{bmatrix}\sigma_{SDL}^2 & \sigma_{E,SDL}\\ \sigma_{E,SDL} & \sigma_E^2\end{bmatrix} = \begin{bmatrix}\lambda_1 & 0\\ \lambda_3 & \lambda_2\end{bmatrix}\begin{bmatrix}\lambda_1 & 0\\ \lambda_3 & \lambda_2\end{bmatrix}^T\right)$	λ_1	5.15	0.644	8
	λ_2	0.101	0.0164	6.16
	λ_3	-0.531	0.406	-1.31
	Covariance matrix elements			
Variance of β_{E_n}	σ_E^2	0.292	0.432	0.68
Variance of β_{SDL_n}	σ_{SDL}^2	26.5	6.63	4
Covariance of β_{E_n} and β_{SDL_n}	$\sigma_{E,SDL}$	-2.735	2.06	-1.33
Number of estimated parameters	31	33		
Number of observations	1056	1056		
Number of individuals	88	88		
Null log-likelihood	-2207.224	-2207.2		
Final log-likelihood	-1193.408	-1158.9		
Likelihood ratio index, ρ	0.459	0.475		
Adjusted likelihood ratio index, ρ_{adj}	0.445	0.46		

(*) Appendix D provides reference tables with the definitions of the variables

5.6 Summary and conclusion

In this chapter data from choice experiment 1 and choice experiment 2 was used to estimate discrete choice models for electric vehicle use scheduling and charging choices. In SCE1, data was used for modelling charging choices when the charging option does not disrupt EV drivers' travel patterns, whereas SCE2 data was used to model charging choice in situations in which the duration of the charging operation may cause schedule delays.

This modelling study sought to meet the following objectives:

- Estimates for the marginal utilities for the salient attributes of the charging and tour timing choice analytical framework presented in Chapter 4.
- The analyses presented also offer an insight into charging choices in the context of smart charging operations:
    - The results show a significant heterogeneity in taste for charging choice attributes.
    - Part of this heterogeneity, specifically in the taste for available energy, could be modelled as a dependent of the latent construct range anxiety.

The marginal utility for available energy was found to significantly increase depending on the expected travel distance and, as mentioned, part of the heterogeneity in taste for available energy was also found to be associated to range anxiety.

The mixed logit estimation of SCE1 revealed a large variability in the charging time coefficient, which implied a positive sign across a large share of respondents. If this is not purely an effect of the choice experiment, it reveals that fast charging operations for home charging may not be required and that load flexibility may be achieved without discouraging through pricing "uncontrolled charging behaviour" (i.e. charging one's EV right after arriving home as fast as possible). Indeed, the results suggest that when users are allowed to choose the time at which their EV should be charged (to the preferred level), they may not necessarily choose the fastest option.

The schedule delay late was also found to vary across individuals and tour characteristics.

An important implication of the heterogeneity in charging behaviour uncovered here is that analyses of the impact of electric vehicle deployment obtained by making use of charging behaviour scenarios should be interpreted with caution. Individual preferences and specific travel needs may induce EV drivers to respond differently to demand response measures, and therefore charging behaviour scenarios designed to represent the effect of such measures in impact analyses may greatly overestimate their effects.

The main limitation of the analytical results presented here is that they are not readily generalised to the entire population of UK drivers since the dataset that it was possible to collect was not representative.

Moreover, the number of survey respondents was 88, the available number of choice situation in each of the choice experiment was 1056. This sample size allowed the estimation of significant effects in all models however, the small number of respondents available may affect the stability of some of the parameter estimates (specifically of some of the interaction terms between individual or tour characteristics and charging choice attributes). This is particular evident when some effects significant in the MNL models become insignificant in the mixed logit specification. Larger sample sizes may be required to confirm the stability of the significant effects indentified in this work.

Notwithstanding, the present results provide useful insights into charging behaviour which could form a basis from which to extend the data collection to a more representative set in order to confirm the findings.

The analyses presented in this chapter were carried out separately for data from the two choice experiments. In contrast, in the next chapter, a demonstration of the application of a response model based on the analytical framework developed will be given based on model parameters obtained from a joint estimation of the data from the two choice experiments.

Chapter 6 APPLICATION DEMONSTRATION: ANALYSIS OF EV LOAD FLEXIBILITY

6.1 Introduction: EV load flexibility and smart charging

Most concepts for the implementation of smart charging make use of an aggregator or charging service provider (CSP), a central entity that "manages the charging of multiple EVs and leverage the flexibility in time of charge to lower the total cost of charging" (Sundstrom and Binding, 2011). On the one hand, CSPs will offer electric vehicle drivers a basic energy service that can be thought of as ensuring a guaranteed amount of energy available in the vehicle battery at a certain time, according to the driver's requests. On the other, CSPs need to regulate the charging operations of all the client vehicles so that grid constraints are satisfied and/or the overall charging activity is optimised along one or more dimensions (e.g. total cost).

The effectiveness of this second function (in fact a service to the grid) depends on the leeway allowed by each charging request in the delivery of the energy to the plugged-in vehicles.

In other words, the operational management algorithms that CSPs need to implement imply taking advantage of the EV fleet flexibility. In order to incentivise requests characterised by lower average charging power (i.e. longer plug-in time, for a given amount of energy charged), the CSP may use price signals (Bessa and Matos, 2012b, Bessa and Matos, 2012c).

More precisely, Bessa and Matos (2012a) define a flexible EV load as: "a client who allows the aggregator to control the charging process (bidirectional communication), which means that its charging requirement must be satisfied, but a degree of freedom exists regarding the supply periods". Whereas an inflexible EV load is a "client who does not allow the aggregator to control the charging process, the aggregator being just an electricity provider".

Using the conceptual model of charging choice developed in this study and defined in Chapter 3, charging choices that correspond to an inflexible and a flexible load are shown in Figure 27. The figure shows the charging choice space: on the y-axis the available energy in the EV battery (E) and on the x-axis the charging duration (CT). If a charging option is chosen so that the energy must be delivered at the maximum charging power as soon as the EV is plugged-in upon arrival at the charging facility, the charging option implies a flexible load. The choice implying an inflexible load (E_k, CT_k), clearly does not allow a charging service provider to control the charging process by defining a charging profile. Whereas the choice implying a flexible load (E_j, CT_j) gives the charging service provider room for manoeuvre in defining a charging schedule from an implemented operational management algorithm.

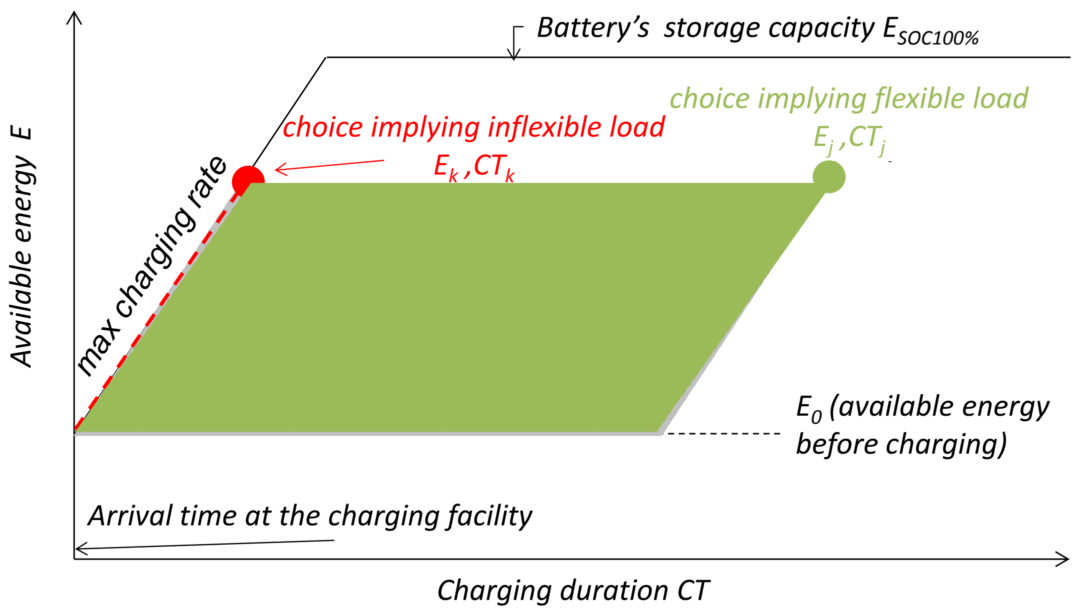

Figure 27 Individual charging choices and load flexibility

The modelling framework developed in this thesis allows us to attempt to quantify the extent to which drivers' charging prefences allow electric grid load flexibility

In this chapter, the model developed in Chapter 3 is estimated by pooling data from choice experiment 1 and choice experiment 2. It is then implemented in a micro simulation framework that uses baseline vehicle activity patterns as inputs, simulates charging choices jointly with activity timing choices, and produces as an output adapted vehicle patterns (with possibly modified timings) together with charging requirements for each home charging opportunity. This simulation tool is then applied, for demonstration purposes, to analyse the flexibility of home charging electric vehicle load under different electricity tariff scenarios.

The next section details the development of the choice model used in the simulation. Section 1.3 provides details of the general simulation framework. Section 1.4 gives the specific assumptions and electricity price scenarios adopted in this application. The results are presented and discussed in section 1.5. The chapter ends with a summary and conclusions.

6.2 Development of a response model for simulations

This section presents the estimation of a model that combines observations from choice experiment 1 (SCE1) and choice experiment 2 (SCE2). The estimated model is then used in the micro-simulation framework presented in the following section.

Recall the home based tour version of the joint model for EV use scheduling and charging (EVUSC) choice that was presented in section 3.4.3. For, the systematic utility for an EVUSC alternative is repeated here:

$$\begin{aligned} V &= \beta_{SDL}SDL+\beta_{DL}DL + \beta_{SDE}SDE+\beta_{PI}PI+\beta_{PD}PD \\ &+ \beta_{TT}(TT_{out} + TT_{in}) + \beta_{SDL}CISDL + \beta_{CT}CT * \delta_{CISDL} + \beta_E E \\ &+ \beta_{COST}(TC_{out} + TC_{in} + CC) \end{aligned} \tag{6.1}$$

where the terms in the expression above are defined in Chapter 3 subsection 3.4.3.

In the previous chapter it was shown how using observations from SCE1 and SCE2, it is possible to estimate parameters: β_E, β_{CT}, β_{SDL}, β_{DL}, β_{COST} and β_{PD}. The marginal utility of travel time (β_{TT}), early schedule delay (β_{SDE}) and activity participation increase (β_{PI}) cannot be estimated using the ECarSim data, since variations in these two attributes were not considered in the choice experiments. Moreover, from the choice experiments' data the cost parameter is estimated only based on variation in the charging costs, since variation in other travel costs were not included in the experimental design.

Using only the choice experiment data, therefore, a simplified version of the model in equation (6.1) that does not take into account the effect of variation in travel times and costs can be estimated and utilised in order to simulate electric vehicle charging patterns. Acknowledging these limitations, such a model is estimated and used in this chapter to demonstrate how it can be applied within a simulation framework.

6.2.1 Model estimation from mixed choice experiment 1 and 2 data

In order to combine observations from SCE1 and SCE2, the difference in scale of the utilities corresponding to the two different datasets needs to be accounted for. To do this in addition to the actual model parameters, a scale parameter that multiplies the utility of the data from SCE1 is estimated. In essence, we treat SCE1 as being pooled with SCE2, as is typically done for discrete choice model estimation from mixed revealed preference (RP) and stated preference data (SP), in which, based on the data enrichment paradigm, SP data are pooled to enrich RP information. Here we use SCE1 to enrich SCE2. The data enrichment paradigm requires that at least one parameter is common between the datasets being pooled. In the present case, the parameters that are common to both datasets are the available energy and the charging cost. The methodology and the relevant literature on estimation of discrete choice models using multiple data sources is discussed in more detail in Appendix C. This discussion focuses specifically on model estimation using SP and RP data, as these are the two data types most frequently used in joint estimation.

In the model estimation using both datasets, scaling the SCE1 utility has the effect of forcing it to have the same scale as in SCE2. In this way, all the parameters estimated in the SCE1 environment are consistent with the SCE2 environment, including those parameters that are estimated only using SCE1 data (i.e. β_{CT}). In mixed RP-SP estimation, the SP-specific parameters are forced to be consistent with RP parameters since, for prediction purposes, the RP environment is the reference environment because it reflects real behaviour. In the present case, in which only SP data is available, we consider the SCE2 environment as the reference because it can be considered to reflect "closer-to-real" behaviour for two main reasons:

- ECarSim respondents (who are normal vehicle drivers and not specifically EV drivers) are likely to have experienced travel choices involving schedule delays: SCE2 embeds the fully hypothetical charging choice into the setting of a potentially more familiar departure time choice context;
- While SCE1 does not allow escape alternatives, i.e. forces a choice between the two alternatives presented, SCE2 has a wider choice set that includes alternatives to the two charging strategies presented.

In a partial preference homogeneity approach to data enrichment,[50] the parameters from the secondary dataset (usually the SP dataset, in the mixed RP-SP case) should not be multiplied by the estimated scale parameter in the forecasting model. Doing this would provide the measure of such a parameter in the secondary dataset environment, whereas, for prediction, the appropriate model should be consistent with the reference or primary environment (the RP environment) (Cherchi and Ortuzar, 2006). Following this approach for the present case, in the simulation model, both SCE1 specific and common parameters will not be multiplied by the SCE1 scaling parameters, in order to allow the prediction mode to "work" in the SCE2 "closer-to-real" environment.

6.2.2 Detailed model specification and estimation results

The models estimated in chapter 6 from the two separate datasets of SCE1 and SCE2 highlight strong heterogeneity in charging behaviour resulting from the choice situation characteristics (e.g. tour characteristics, ambiguity in tour feasibility etc…) as well as idiosyncratic preferences (partially captured by individual characteristics).

For the current implementation, a parsimonious specification is adopted in which only the planned tour driving distance d_n is used to capture systematic taste variation in available energy coefficients. Moreover, the error structure specification is maintained as an IID extreme value type I so that an MNL model can be estimated. This simple MNL formulation is computationally attractive; however, as mentioned several times in this dissertation, it is affected by the independence of irrelevant alternatives (IIA) property. IIA means that the addition of a new alternative to the choice set, or a variation in the attribute value of a non-chosen alternative, does not affect the relative odds of choice between the other alternatives. This may be a limitation in the present case, since it implies the absence of an increased substitution rate between adjacent energy levels, (or adjacent charging durations, or adjacent departure times), compared to energy levels (charging durations, departure times) that are far apart from each other. This means for example that, under IIA, introducing a lower tariff to promote charging durations above 10 hours generates a proportionate decrease in the probability of the choice of 10 hours charging duration and 5 hours charging duration. We

[50] A partial preference homogeneity approach entails the estimation of some of the parameters from one data source, some from the other.

would expect instead disproportionate decreases. Notwithstanding this caveat, the MNL structure is adopted for the purpose of demonstrating the application of this model.

The utilities are thus specified as follows:

$$U_{nsi}^{SCE1} = \lambda^{CE1}\left(\beta_E E_{nsi}^{SCE1} + \beta_{E_{d_n}} d_n E_{nsi}^{SCE1} + \beta_{CT} CT_{nsi} + \beta_{CC} CC_{nsi}^{SCE1} + \beta_{FFC_{NACS}} FFC_{nsi} NACS_{ns} + \beta_{FFC} * FFC + \epsilon_{nsi}^{CE1}\right) \tag{6.2}$$

$$U_{nsi}^{SCE2} = \beta_{EV} EV + \beta_E d_n E_{nsi}^{SCE2} + \beta_{SDL} CISDL_{nsi} + CC_{nsi}^{SCE2} + \beta_{DL} DL_{nsi} + \beta_{PD} PD_{nsi} + \epsilon_{nsi}^{CE2} \tag{6.3}$$

$$U_{NT}^{SCE2} = \beta_{NT} NT + \beta_{PD} T_{D_n}^{*} + \epsilon_{nsi}^{SCE2} \tag{6.4}$$

$$U_{OM}^{SCE2} = \beta_{OM} OM + \epsilon_{nsi}^{SCE2} \tag{6.5}$$

where indices n, s and i indicate respectively the individual, the choice situation and the alternative. The other terms in the expressions above re defined as follows

- U_{nsi}^{CE1} is the utility for a charging choice alternative in SCE1;
- λ^{CE1} is the scale parameter;
- E_{nsi}^{CE1} is the available energy after charging in SCE1;
- d_n is the distance for the prospective tour after charging ;
- CT_{nsi} the charging duration (in SCE1);
- CC_{nsi}^{CE1} is the charging cost in SCE1;
- FFC_{nsi}a dummy variable indicating an alternative in which the vehicle is charged at the maximum charging power in SCE1;

- $NACS_{ns}$ indicates a choice situation with no ambiguity in tour feasibility;
- EV is a dummy variable indicating the EV use and charging alternatives (in SCE2)
- E_{nsi}^{CE2} is the available energy after charging in SCE2;
- $CISDL_{nsi}$ is the charging induced schedule delay (in SCE2);
- CC_{nsi}^{CE2} is the charging cost in SCE2;
- DL_{nsi} is a dummy variable indicating a non-zero schedule delay (in SCE2);
- PD_{nsi} is a decrease in activity participation at the main tour destination (in SCE2);
- NT is a dummy variable indicating the "no charging and no travel alternative" in SCE2
- $T_{D_n}^{*}$ is the original activity participation time at destination[51] , in SCE2
- OM is a dummy variable indicating the "no charging and shift mode" alternative (in SCE2)
- β_X where X is a generic subscript are utility coefficients;
- ϵ_{nsi}^{CE1} and ϵ_{nsi}^{CE2} are error terms in SCE1 and SCE2 respectively.

Note that in the expression above superscripts SCE1 and SCE2 are placed only to attributes that are common to both datasets in order to identify from which dataset their level are taken, since the other non-common attributes have an obvious origin. λ_{CE1} is the scale parameter that is obtained in the mixed estimation.

Table 24 reports the parameter estimates from the mixed estimation.

The parameters that were not found to be significant are not retained in the final specification. In addition also alternative specific constants for the options to curtail activity participation time at destination in SCE2 are estimated (A1, A2, A3, A4, B1, B2, B3 and B4). However these are not included, in the model used for simulation, as, these only capture the shares of the four participation decrease options in SCE2 between option 1 and option 4 either in alternative A or B. These have no meaning in the simulations where both the charging and activity decrees option at destination are different in number from in the choice experiment. The parameters that are used in the simulations are summarised in subsection 6.2.4.

[51] In the "no charging and no travel alternative", the activity participation time decrease at destination coincides with $T_{D_n}^{*}$

Table 24 Logit estimation using SCE1 and SCE2 jointly

	Preliminary specification			Final specification		
Variable	Coefficient	Std err	t-test	Coefficient	Std err	t-test
A1	-0.173	0.161	-1.07	0	fixed	
A2	-1.14	0.224	-5.1	-1.09	0.209	-5.22
A3	-1.22	0.23	-5.31	-1.18	0.217	-5.41
A4	0.00623	0.115	0.05	0	fixed	
A_SC1	0	fixed		0	fixed	
B1	-0.0341	0.159	-0.22	0	fixed	
B2	-1.23	0.237	-5.18	-1.18	0.222	-5.34
B3	-1.49	0.263	-5.66	-1.45	0.25	-5.78
B4	0	fixed		0	fixed	
B_SC1	-0.0076	0.0358	-0.21	0	fixed	
EV	6.05	0.705	8.58	6.01	0.678	8.86
EV* Distance [100miles]	-10.4	1.77	-5.88	-10.5	1.7	-6.2
NT (no charging and no travel)	0	fixed		0	fixed	
OM (no charging and travel with other mode)	1.21	0.291	4.17	1.15	0.277	4.13
PD [h]	-0.134	0.0524	-2.57	-0.151	0.0499	-3.02
CC [£]	-0.202	0.0255	-7.92	-0.201	0.0249	-8.07
FFC	0.0278	0.104	0.27	0	fixed	
FFC * NACS	-0.994	0.186	-5.35	-0.974	0.167	-5.85
E*[kWh]	-0.109	0.0251	-4.33	-0.11	0.0238	-4.63
CISDL [h]	-0.827	0.135	-6.14	-0.812	0.134	-6.06
E * Dist [kWh*100miles]	0.498	0.0784	6.36	0.503	0.075	6.71
CT10h*[10h]	-0.0955	0.0354	-2.7	-0.0993	0.0327	-3.03
DL	-1.94	0.2	-9.68	-1.99	0.192	-10.38
Scale1	2.12	0.315	3.57	2.13	0.313	3.61
Number of estimated parameters	21			16		
Number of observations	2112			2112		
Null log-likelihood	-2939.2			-2939.2		
Final log-likelihood	-2057			-2057.8		
Rho-square	0.3			0.3		
Adjusted rho-square	0.293			0.294		

6.2.3 Validation of the model

We carry out below a simple form of validation using a hold-out sample. While more powerful approaches, such as multiple cross-validation, exist, the simple hold-out sample approach is deemed sufficient here to investigate the capability of the choice model to reproduce observed market shares.

The restricted model is validated by partitioning the sample between an estimation subsample (~80% of size of the complete sample) and a hold-out subsample. For the first, the model specification in Table 1 is re-estimated, while for the hold-out sample the estimated model is used to predict the choices for choice situations. For validation, predicted choices and observed choices in the hold-out sample are compared, as shown in Table 26. Overall, the shares of the predicted alternatives closely match the observed shares, with the root mean squared error between the observed and the predicted share being ~1%.

Table 25 Model estimates from the estimation subsample

Variable	Coefficient	Std err	t-test
A1	0	fixed	
A2	-1.08	0.228	-4.72
A3	-1.29	0.251	-5.14
A4	0	fixed	
A_SC1	0	fixed	
B1	0	fixed	
B2	-1.2	0.245	-4.91
B3	-1.53	0.285	-5.38
B4	0	fixed	
B_SC1	0	fixed	
EV	5.59	0.717	7.8
EV* Distance [100miles]	-9.67	1.79	-5.42
NT (no charging and no travel)	0	fixed	
OM (no charging and travel with other mode)	0.995	0.298	3.34
PD [h]	-0.159	0.0543	-2.93
CC [£]	-0.198	0.0273	-7.26
FFC	0	fixed	
FFC * NACS	-1.1	0.205	-5.35
E*[kWh]	-0.0985	0.0248	-3.97
CISDL [h]	-0.778	0.146	-5.33
E * Distance [kWh*100miles]	0.469	0.0787	5.96
CT10h [10h]	-0.108	0.0367	-2.94
DL	-1.99	0.212	-9.38
Scale1	2.16	0.357	3.24
Number of estimated parameters	16		
Number of observations	1716		
Null log-likelihood	-2399.7		
Final log-likelihood	-1677.2		
Rho-square	0.301		
Adjusted rho-square	0.294		

Table 26 Model validation: predicted and observed shared for the hold out subsample

Alt.	Observed counts	Predicted counts	Observed shared	Predicted shared
1	111	108	28%	27%
2	96	99	24%	25%
11	13	14	3%	4%
12	4	5	1%	1%
13	6	4	2%	1%
14	44	49	11%	12%
21	13	14	3%	3%
22	4	4	1%	1%
23	4	3	1%	1%
24	49	50	12%	13%
33	4	7	1%	2%
34	48	40	12%	10%
Tot	396	396	100%	100%
	rms	3.36972	rmse	0.00851

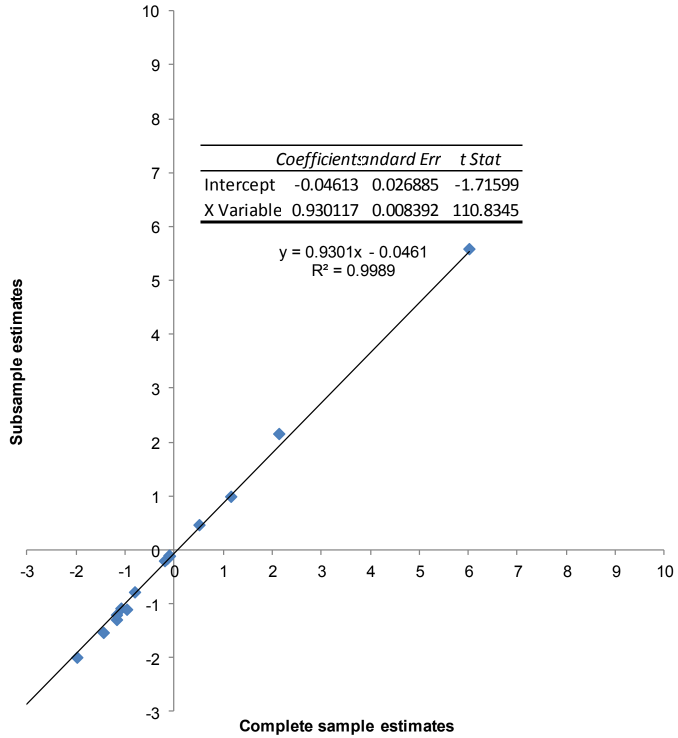

Figure 28 Comparison between the full sample estimates and estimates from the subsample used for the model validation

Table 27 Difference between estimates from full sample estimation and subsample estimation

Variable	t stat of estimates differences
A2	-0.05
A3	0.51
B2	0.09
B3	0.32
EV	0.62
EV * dist [100mi]	-0.49
OM (no charging and travel with other mode)	0.56
PD [h]	0.16
CC [£]	-0.12
FFC * NACS	0.75
E*[kWh]	-0.48
CISDL [h]	-0.25
E * Dist [kWh*100miles]	0.45
CT10h [10h]	0.27
DL	0.00
Scale1	-0.10

To confirm that the validation applies also to the model estimated with the full dataset, Figure 28 compares model estimates with those obtained from full sample estimation: they approximately align on a 45 degrees line passing close to the origin (the intercept estimate is significantly different from zero only at the 10% level). Furthermore, Table 27 shows the t-statistics for the difference between the estimates from the subsample with estimates from the full sample. The null hypothesis that the difference is equal to zero cannot be rejected for any of the model parameters. The visual test and the t-tests suggest that the estimated parameters are the same. It can thus be concluded that the validation carried out on the 80% size subsample could be extended to the full sample.

It should be noted that the validation above only shows that the model reproduces with reasonable accuracy the data generation process in the two choice experiments of ECarSim. To prove the external validity of the model, revealed preference data will need to be collected and the model validated using this data. Ideally, the current model should be enhanced with a mixed estimation using both stated and revealed preference data, and the enhanced model re-validated using a hold-out revealed preference sample.

6.2.4 Parameters used in the simulation model

Not all the parameters estimated and shown in Table 24 were used for the simulation:

- Parameters capturing the share of the activity participation decrease options in SCE2. These have no meaning in the simulations where both the charging and activity decrees option at destination are different in number from in the choice experiment.
- as already discussed, the scale factor is not used in the simulation.

An assumption also needs to be made regarding the distance dependent marginal utility for those distance levels in the model application that fall outside the range of tour distances within the estimation sample (30-80 miles). For distances above this range it is assumed that the marginal utility has the same distance dependence as that in the estimated model. For distances below this range, this assumption cannot be applied because, for distances below the range of variation of the estimation sample, the obtained estimates provide implausible negative marginal utilities for available energy. A negative marginal utility for available energy would mean that, all else being equal, there is a preference for lower range. Since the analyses in Chapter 5 have shown that there is a general preference for higher available energy,[52] we here adopt the hypothesis that this remains true even for lower distances.

Based on the estimates of the final specification in Table 24, the marginal utility for available energy becomes negative for tour distances below 22 miles. Recall that the range of variation of tour distances within the estimation sample is 30 to 80 miles, thus within this range the marginal utility has the correct sign. If the model is also to be used for lower distances, however, a plausible assumption that avoids a negative marginal utility for available energy is needed. The assumption that is made is that the marginal utility grows linearly from zero at zero tour distance to the value implied by the estimated model at 30 miles.

Table 28 provides the parameter estimates effectively used in the simulation model

Table 28 Parameters kept in the simulation model

Variables included in the simulation model	Coefficient
EV	6.01
EV* Dist [100miles]	-10.5
NT (no charging and no travel)	0
OM (no charging and travel with other mode)	1.15
PD [h]	-0.151
CC [£]	-0.201
FFC * NACS	-0.974
SDL [h]	-0.812
CT10h*[10h]	-0.0993
DL	-1.99
E*[kWh] (for Dist>=30 miles)	-0.11
E * Distance [kWh*100miles]] (for Dist>=30 miles)	0.503
E*[kWh] (for Dist<30 miles)	0 (*)
E * Dist ance[kWh*100miles]] (for Dist<30 miles)	0.136(*)
(*) based on the assumption discussed in the present section	

[52] Except for the specific case highlighted in SCE1, of choice situations without ambiguity in tour feasibility, in which a significant share of individuals tend to avoid the option to fully charge at the fastest speed. The specification adopted here (Table 24) takes this fact into account.

6.3 Simulation framework

In this section we present a simulation framework that is intended to model the demand activity-travel and charging response to pricing of electricity. This framework makes use of the model above to simulate charging and time of travel choices under various pricing of electricity tariff structures for electric vehicle charging.

It should be pointed out that we focus here on the demand side only, with supply side considerations not being addressed. In other words, for the sake of simplicity, situations such as competition between electric vehicle users for access to limited charging infrastructure, or distribution network capacity (which may be significant in large EV deployment scenarios) are neglected here.

The simulation process takes the following as inputs:

- Existing vehicle diaries typically extracted from national or regional travel surveys;
- Electric vehicle penetration and technology scenarios, i.e. scenarios prescribing the share of electric vehicles characteristics (namely maximum recharging power, and battery capacity), and the availability of electric vehicles to households;
- Charging infrastructure availability and characteristics scenarios: these prescribe the availability of recharging infrastructure at various locations visited by drivers (e.g. home, work, or others), and the charging power available at the recharging facility;
- Electricity tariffs for charging: e.g. time of day tariffs, flat tariff, or tariffs based on the charging power.
- Observed vehicle diaries available from travel surveys are used as baseline patterns: they provide travel distances and reference timings to calculate schedule delays and activity participation penalties (in fact, in principle, this response model could be integrated within an activity based model, which would generate the input baseline vehicle patterns).
- The charging infrastructure availability scenarios are used to identify the charging opportunities and the corresponding activity-travel episodes (COATE).[53] Drivers are assumed to make independent charging and timing decisions for each COATE. This assumption has a relevant behavioural implication: it implies a myopic charging

[53] See Figure 9 and Figure 10 in Chapter 3.

behaviour. This means that individuals make their charging choices without thinking about future charging opportunities in which, for instance, the electric vehicle charging price may be higher or lower. This is indeed a defining assumption of the joint charging and activity travel timing choice modelling framework as it is developed in Chapter 3.

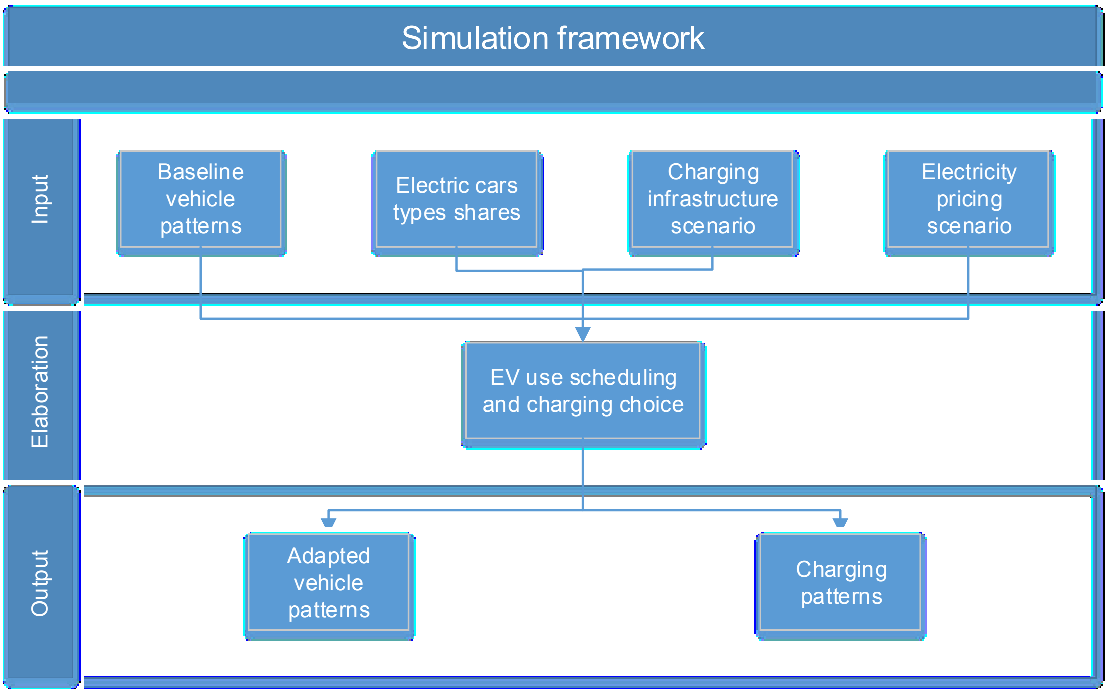

Figure 29 Simulation framework

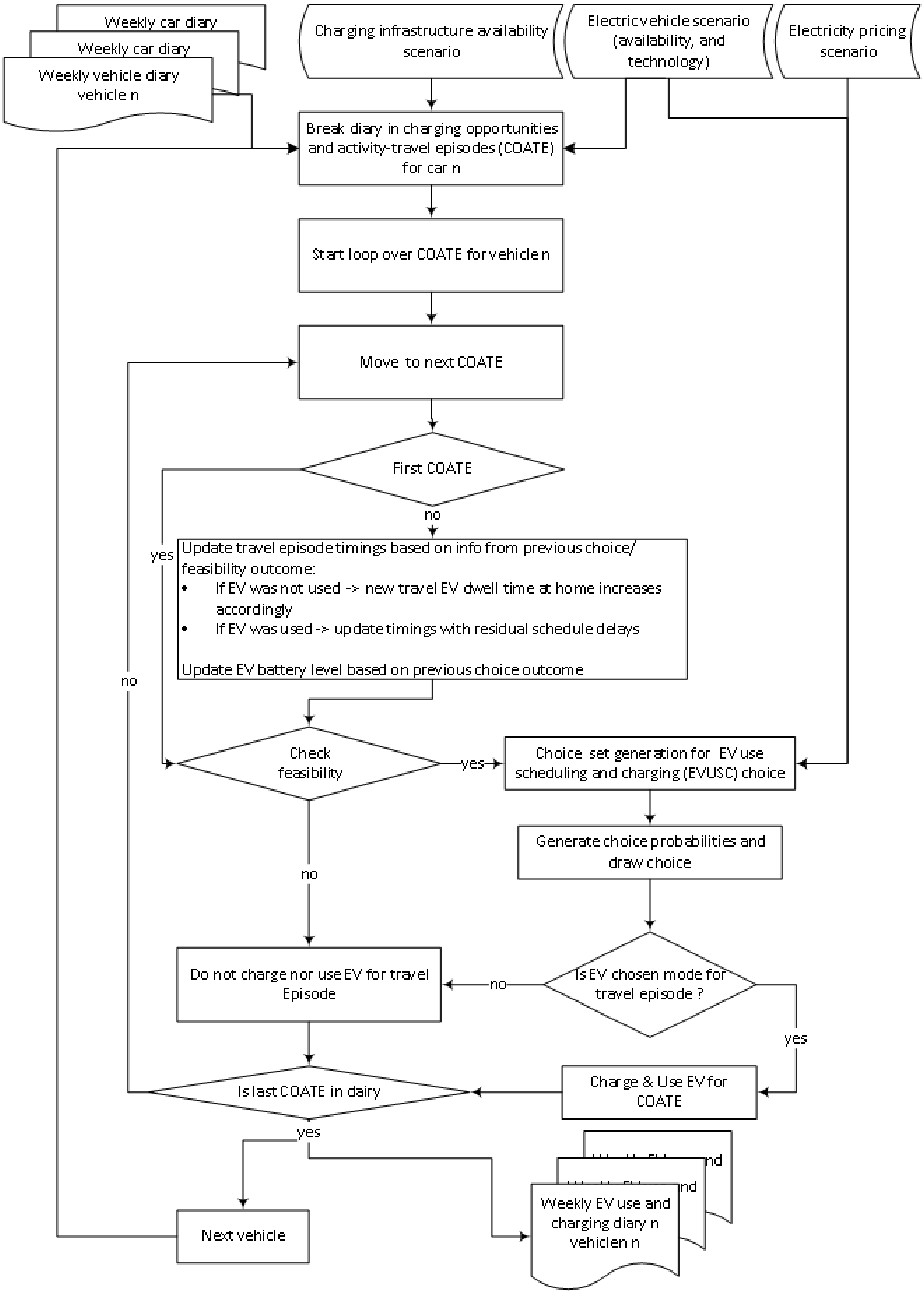

Figure 30 Simulation process' flow chart

The vehicle and the infrastructure characteristics at a charging opportunity, together with the travel distance following the charging opportunity allow us to define the choice set for the charging choice, i.e. the feasible battery levels for completing the travel episode. If a travel episode is unfeasible, the electric vehicle is assumed to skip it and remain at the origin until the next travel episode starting from the same location. Assumptions about the energy consumption rates over each travel episode are also needed to update the energy level after travelling and to calculate the minimum energy requirement to make the next travelling episode feasible. Figure 29 shows the simulation framework. Figure 30 shows the simulation process flow in more detail. A (weekly) vehicle diary is broken into COATEs and, for each COATE, the feasibility is checked based on the range of the vehicle specified by the EV scenario (battery size and consumption rate). If the COATE is not EV feasible then it is assumed that the EV does not leave its current location. If the COATE is EV feasible, then an EV use scheduling and charging decision is simulated, the outcome of the decision is a charging option (including no charging) and an EV use schedule for the current COATE, or a decision not to charge and not to use the EV. If the current COATE is not the last in a vehicle's diary, then the simulation moves to the next COATE. The COATE is updated based on the outcome of the feasibility or the decision. If the vehicle did not move from the origin then the COATE is updated such that the charging option can include charging durations that last throughout the vehicle dwell time at the current location. If the vehicle was used and arrived at its current location with a delay the COATE is updated accordingly. Similarly, the state of charge of the battery is updated according to the previous charging choice and the subsequent use, before arrival at the current location.

6.3.1 Simulation outputs

The simulation outputs are:

- Modified tours, i.e. with possible schedule delays (late) and with participation durations in the main tour activity possibly curtailed;
- Chosen charging option for each charging opportunity.

Several charging profiles may be compatible with a chosen charging option, if the chosen charging option allows flexibility, i.e. if it does not require charging at the maximum available rate as soon as the vehicle arrives at the charging facility. Thus, for the cases where chosen charging patterns allow flexibility, the charging service providers can generate charging profiles that optimise their operations. While this simulation tool does not undertake such an optimisation of the electricity supply, the results do show the extent of load flexibility compatible with the modelled charging choices under various pricing scenarios.

6.4 Simulation assumptions and scenarios

6.4.1 Baseline vehicle patterns

The baseline vehicle patterns that will be used here are weekly vehicle diaries obtained from a subset of the National Travel Survey (NTS). The NTS is a continuous survey on personal travel patterns in Great Britain. Data is collected via face-to-face interviews and seven day travel diaries. This allows a link between travel patterns and individual characteristics.

A specific feature of the NTS is that journeys carried out by members of the same household by driving a specific vehicle from the household's vehicle holding can be identified, based on stage level information. It is possible, therefore, to construct seven day vehicle diaries from seven day travel diaries from individuals belonging to the same household. The vehicle diaries used in the present chapter were extracted from the NTS by a Master's student at the Centre for Transport Studies at Imperial College London who, for her Master's project, developed a procedure to extract car diaries from the NTS dataset and organise them in home based tours (Song, 2013). The car diary extraction from the various NTS data files follows the workflow specified in Figure 31.

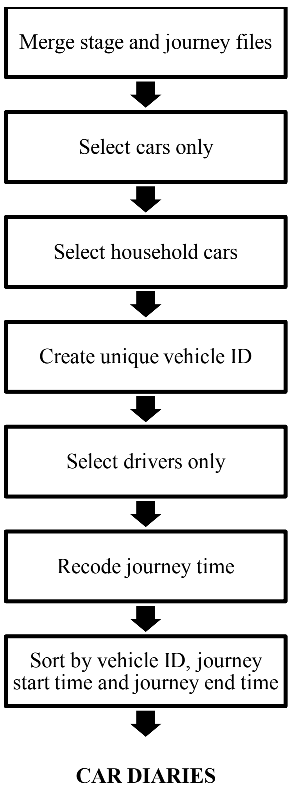

Figure 31: Work flow to extract car diaries from the NTS,(Song, 2013)

For the practical purpose of limiting the running time of the simulations presented in this chapter it was decided only to use a subsample of car diaries from the NTS 2010. Instead of selecting random vehicle diaries it was decided to keep only the vehicle diaries of households resident in the London Boroughs. This geographical area was chosen for two reasons. Firstly, it tallies with the residential location of the majority of individuals in the ECarSim sample used to estimate the model parameters. Secondly, to allow comparison of (scaled) simulation results with available aggregated domestic power demand data for London.

The distribution of tour distances in the 2010 London Boroughs subsample of 643 car diaries is shown in Figure 32 with a large proportion of vehicle tour distances (82%) being less than 20 miles. Since the choice model was estimated on a sample in which the tour distances varied over an interval of between 30 and 80 miles, the assumption provided in section 6.2.4 for the calculation of the marginal utility of available energy for tour distances below 30 miles will affect a large majority of the COATEs in the simulation. Indeed, the fact the there is a disparity in the distance distribution between the simulation sample (London Boroughs) and the estimation sample (ECarSim), is the result of a design decision for ECarSim's choice experiments: charging choices before tours of length of a considerable fraction of the EV driving range would ensure (with reasonable confidence) enough relevance to the charging choice[54].

[54] The reasons for choosing 30 to 80 miles tour distance limits in the estimation sample are discussed in Chapter 4 section 4.8.

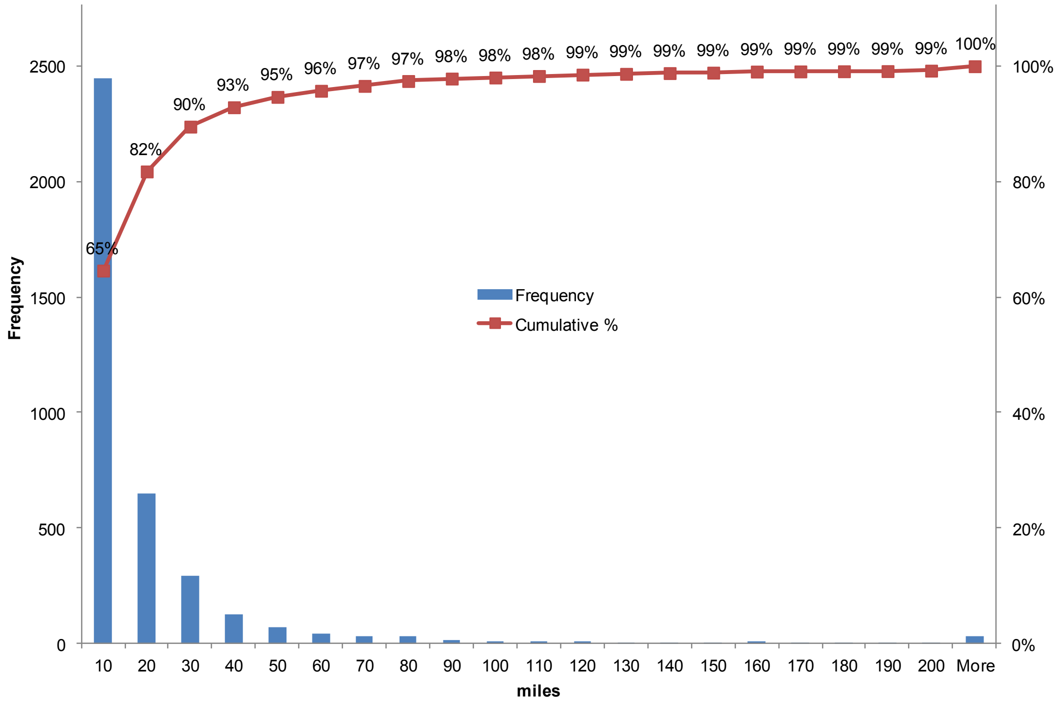

Figure 32 Home-based tour distances carried out by household cars in the London Borough subsample of NTS 2010

6.4.2 Electric cars and charging infrastructure

The following characteristics are used for all electric cars in the simulation:

- Storage capacity of battery: 24kWh
- Consumption: for travel episodes an average consumption of 0.29kWh/mi is assumed

These characteristics are typical of a C-segment (medium size) car such as the Nissan Leaf. In fact, the battery consumption figure corresponds to the combined (urban and extra urban) consumption by a Nissan Leaf according to the standard EPA combined driving cycle (DoE, 2013).

It is assumed that all vehicles can only be charged at the location where they are parked when their drivers are at home (e.g. overnight). For simplicity we refer to this assumption as "home charging". Note that, in London Boroughs, only 9% of overnight parking locations are garages, while 45% are un-garaged private properties and 43% utilise on-street parking (Figure3, Chapter 1). It is recognised, therefore, that the home charging assumption utilised here is quite a strong one, since it entails a widespread network of public on-street charging posts, accessible to drivers who use on-street parking. This assumption is made for simplicity, given the demonstration purpose of this simulation. From a longer term, perspective, however, this scenario might be perceived as less extreme, considering the UK government's goal of "virtually decarbonise the UK fleet by 2050", as mentioned in Chapter 1 (Section 1.2).

The charging power is fixed to 3kW (with the charging efficiency assumed to be 1). This value corresponds to standard charging. The recharging infrastructure is assumed to enable smart charging, however, so that individuals can choose a charging duration[55] and available energy level after charging, within the limits of a maximum average charging power of 3kW.

6.4.3 Further simulation settings

A series of further assumption are required in the simulation and these are summarised below.

CHOICE SET

The available charging alternatives and tour timings for the simulation choice sets are generated considering:

- all energy levels that make the tour feasible after charging, based on 0.75 kWh steps, (note that tours that are not feasible with the full battery capacity are excluded);
- all possible charging durations based on 30 minute time steps within a maximum schedule delay allowed, as detailed later in this section.
- the charging constraints (alternatives that imply average charging powers above 3kW are excluded);
- all participation time penalties (activity participation duration decreases) at the main tour destination based on 30 minute time steps within a maximum level allowed (detailed later in this section); these are available only for charging alternatives that lead to schedule delays.

The "no travel" alternative and the "other mode" alternative are always available in the choice sets (however the model treats them naively based on the specification provided in subsection 6.2.2).

SCHEDULE DELAYS AND ACTIVITY PARTICIPATION PENALTY LIMITS

We constrain the maximum schedule delay to 2 hours. Furthermore, the schedule delay is made available in the drivers' choice sets only if it can be fully recovered in the dwell time at home following the current travel episode. This is done to avoid schedule delays being carried over from one day to the other of the travel week. A maximum of 2 hour long out-of–home

[55] Charging duration is understood as defined in subsection 3.3.1, i.e. as the elapsed time since arrival at the charging facility until the charging operation is completed

activity decreases are allowed so as to (partially) absorb a schedule delay, but only for main out-of-home activities longer than 2 hours.

BATTERY LEVEL AT THE START OF THE TRAVEL WEEK

The battery level at the first charging opportunity of the week is assumed to be equal to the full charge minus the energy consumed in the last travel episode of the week. This is consistent with the boundary condition of periodicity in vehicle diaries that is assumed in extracting the vehicle diaries from the NTS diaries.

6.4.4 Charging electricity tariff scenarios

Simulations are run for the following pricing scenarios.

- Fixed price – the electricity price is constant throughout the day at 0.14£/kWh
- Time of use (ToU) price – the electricity price between midnight and 7am is 0.06£/kWh, while for the rest of the day it is 0.16£/KWh
- Load flexibility – the price is 0.1 £/kWh if the average charging power calculated over the charging duration is less than or equal to half of the nominal charging power of the available home charger, (i.e. if the average charging power is less than or equal to 1.5 kW, given the electric vehicle supply equipment assumption in the simulation). The price otherwise is four times higher.

The first two price scenarios correspond to price structures currently available for domestic electricity in London. The second, in particular, reflects the Economy 7 scheme which is a differential tariff available to UK domestic customers who pay a lower electricity price over a 7-hour period at night time.

The price level for the first price scenario is within the range of variation of the unit cost of electricity for domestic customers in London in 2013 (13.12 to 17.40 p/kWh) as reported by DECC (2013) in the in Quarterly Energy Prices - December 2013.

The price levels of the ToU tariff are broadly coherent with the Economy 7 scheme in London in 2013.[56]

[56] For example, EDF a major supplier in London, in its "Fixed Price 2013 tariff" offered the Economy 7 night rate at 4.97p/kWh and day rate at 14.10 (EDF 2013). The standing daily charge was 23.18 p. For a typical domestic consumption of 3300kWh, one can calculate a per kWh rating of the standing

The third tariff is created to incentivise charging choices that induce a flexible charging load, i.e. that allow flexibility in the charging electricity dispatch. Indeed, any average charging power lower than 3kW in the charging infrastructure scenario of the simulation corresponds to a flexible charging load. The choice of 1.5 kW as the average charging power threshold was intended to increase load flexibility perceptibly compared to the other two pricing scenarios. In fact, the load implied by the charging choices in the first two scenarios is already extremely flexible, as the results will show. The price levels of this third tariff are chosen so that: a) the low price falls between the night price of the ToU tariff and the price level for the fixed price scenario, (b) the high price results in a cost per mile approaching (though remaining lower than) the price per mile of a petrol car in the same class as the Nissan Leaf.[57]

6.5 Results

6.5.1 EV load flexibility implied by charging choices

For each tariff scenario and each vehicle, charging and tour timing choices are simulated for all the COATEs within the travel week. One can therefore calculate, for each vehicle and each charging opportunity, the theoretical minimum charging power compatible with the simulated choices. We name this the *choice based average charging power*, CBACP. The CBACP is the ratio of the amount of energy charged (i.e. the available energy at the end of the charging operation minus the energy before charging) to the charging duration (as defined in this study), implied by the chosen charging option. CBACP weekly patterns for five vehicles in the simulation are shown in Figure 33. The x-axis of the figure indicates the time of the week, the y-axis the CBACP, Lines of different colours correspond to CBACP patterns for different vehicles. When the CBACP is zero, the vehicle is not available for charging; the widths of the non-zero windows in each pattern indicate the chosen charging durations when the vehicle requires charging, their height corresponds to the minimum charging power required to comply with the chosen energy requests.

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charge (2.56p/KWh). From this one can calculate reference night and day time rates that include the standing charges: 7.5p/kWh and 16.66p/kWh. These values are higher than but comparable to those used in the ToU scenario in the simulation (EDF, 2013).

[57] For example the fuel cost for a Ford Focus 1.6 Duratec Ti-VCT (85PS) 5 Door, is rated at £ 1,572 for 12,000 miles, (VCA, 2013). This gives a cost per mile of 13.1p/mile. The cost per mile in the simulation assuming the high cost level in the load flexibility pricing is 11.6p/mile.

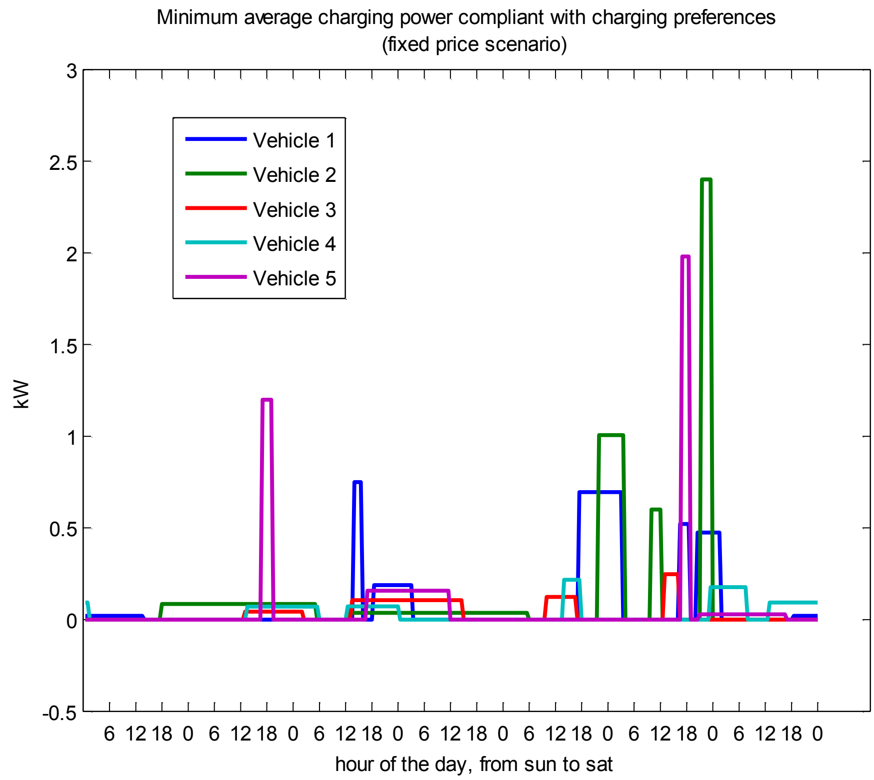

Figure 33: Examples of choice based average charging power patterns

In order to measure the flexibility of a chosen charging option, the CBACP has to be put in relation to the actual (maximum or fixed) charging power supplied by the electric vehicle supply equipment. One could, for example, define the following relation as a formal measure of the flexibility implied by the charging choice:

$$CBCF = 1 - \frac{CBACP}{r^{(max)}} \tag{6.6}$$

where CBCF is the choice based charging flexibility and $r^{(max)}$ is the electric vehicle supply equipment power supply (3kW in the present simulation). This quantity can also be interpreted as the fraction of the chosen charging duration beyond the minimum charging time required to charge the requested amount of energy, i.e. it measures the percentage of "unused" charging duration. This fraction of CT can be used to shift part of the load from charging to a later time period, instead of continuously supply power at the nominal rate as the vehicle reaches the charging facility.

If the charging choice implies an inflexible load, i.e. if the electric vehicle driver chooses to have the vehicle charged to the chosen battery level continuously at $r^{(max)}$, then CBCF will be equal to zero. On the other hand, as the load is more and more flexible, the CBACP grows to approach 1. The meaning of CBCF equal to one needs to be explained: when only electric vehicle charging is allowed, and there is no discharging for vehicle-to-grid (V2G) or vehicle-to-home (V2H) services, then CBCF is undefined at 1, because the CBACP approaches to zero but cannot be equal to zero. In fact, if the vehicle can only receive energy by the charger, a zero average charging power is meaningless because no energy is delivered and therefore no charging duration exists. This lack of meaning arises also mathematically by the indeterminacy in the case of no charging:

$$CBACP = \frac{E - E_0}{CT} = \frac{0}{0} \tag{6.7}$$

When V2G or V2H is allowed the situation is different. In this case, the EV user might want to keep the vehicle grid-connected, in exchange for money or credits, even without a net increase in the battery level for the vehicle. Here, CBACP could be zero and CBCF could be one. Indeed, in V2G or V2H settings, CBACP could be negative and CBCF greater than 1. Although in principle both these cases could be handled by the simulation tool, V2G or V2H paradigms were not considered in the simulations presented here.

Figure 34 shows the distributions of CBCF over the charging choices for the three pricing scenarios. The two most important observations that can be made are the following:

- For all price scenarios, over 90% of the load implied by charging choices is in principle flexible.
- The differences between the scenarios are minimal and the effect of the time-of-use tariff is practically undistinguishable.
- The first observation means that under current price electricity tariffs (fixed price scenarios and ToU- Economy 7 like- scenarios), if the charging technology allowed a choice of the battery level and the time this should be achieved, drivers would only adopt a behaviour similar to that implied by uncontrolled (or dumb) charging

scenarios in a very few cases.[58] In other words, most of the choices would in fact be compatible with a flexible load.

- The second observation suggests that if the technology actually allowed a choice of the time at which the EV should be ready to use, a flexible load could be achieved in various pricing regimes, even those that do not specifically incentivise it. Economy 7 type tariffs imply lower average prices for longer overnight charging durations (since energy delivery starts later than the arrival time at home, the charging duration as defined in this study is higher for cheaper charging alternatives). There is no sensible difference between the CBCF distribution for this case, however, and the fixed priced case. The only noticeable pattern is a slightly lower weight of low flexibilities for the tariff specifically designed to discourage them.

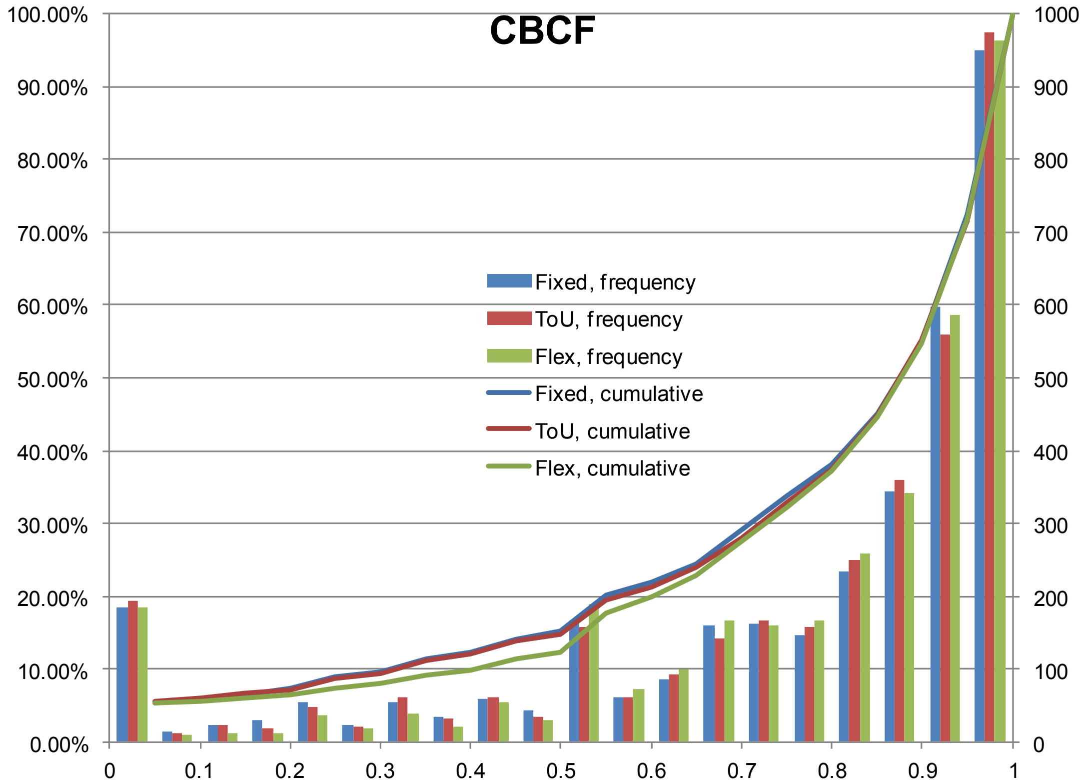

Figure 34: Distribution of the choice based charging flexibility

[58] Recall from Chapter 2, section 2.4 that in uncontrolled/uncoordinated/dumb charging electric vehicles are assumed to start charging at the point of arrival until departure or full charge at the maximum charging power.

These results have two major implications:

1. Uncontrolled charging is the result of technological constraints rather than behaviour: If users are enabled to choose, the impact on the charging load would not be as extreme as implied by uncontrolled charging; according to the present simulation their choices would be compatible with the optimisation of charging schedules.
2. Load flexibility apparently does not need to be strongly incentivised; it is inherent with travel patterns, but *also* compatible with drivers' preferences. Thus charging service providers would not need strong monetary incentives to harvest flexible load.

6.5.2 Actual load on the grid

Depending on the actual charging profiles compliant with the charging choices that are used to recharge the vehicles the load profiles for each vehicle over the week can be generated and aggregated to provide the total load.

If the energy is delivered in the minimum time compatible with the charging choices, the load for the fixed price scenarios and the flexible load scenarios almost coincide with the uncontrolled charging scenario, whereas the time-of-use price scenario presents a very sharp spike at midnight when the low price tariff starts (Figure 35).

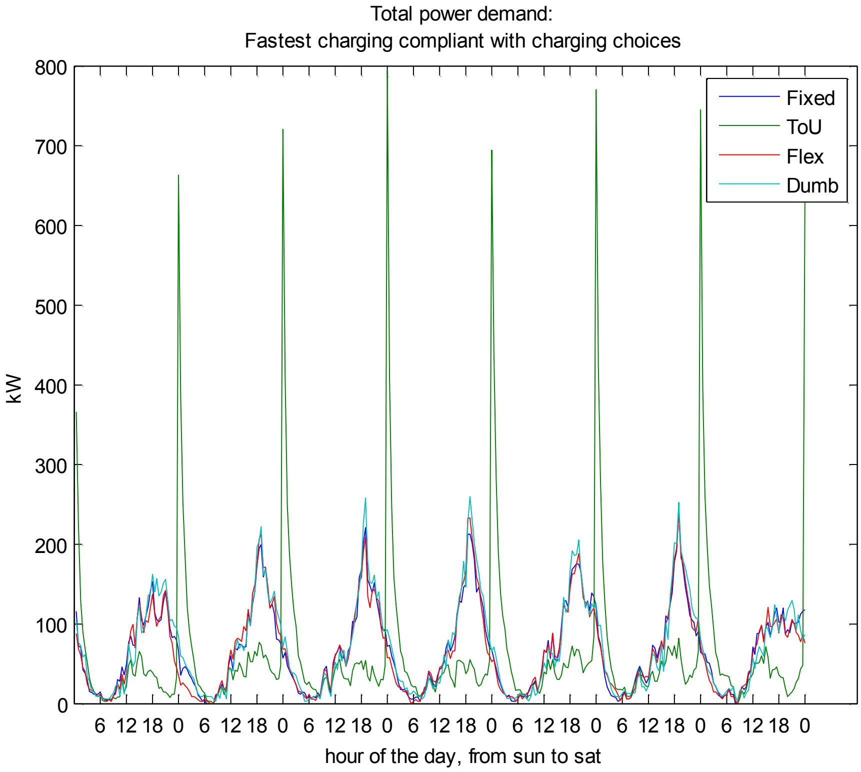

Figure 35 Power demand from home charging delivered in the minimum time compatible with the charging choices

This charging procedure does not take advantage of the choice based charging flexibility, however. Figure 36 shows instead that if the choice based flexibility is taken advantage of, by simply initiating the delivery of energy at random times within the chosen charging duration, while still complying with charging choices, the peaks in load are considerably reduced, both in the fixed and flexible pricing scenarios, compared with the uncontrolled charging scenario. Concerning the time-of-use price scenario the sharp spike is changed into a smoother peak.

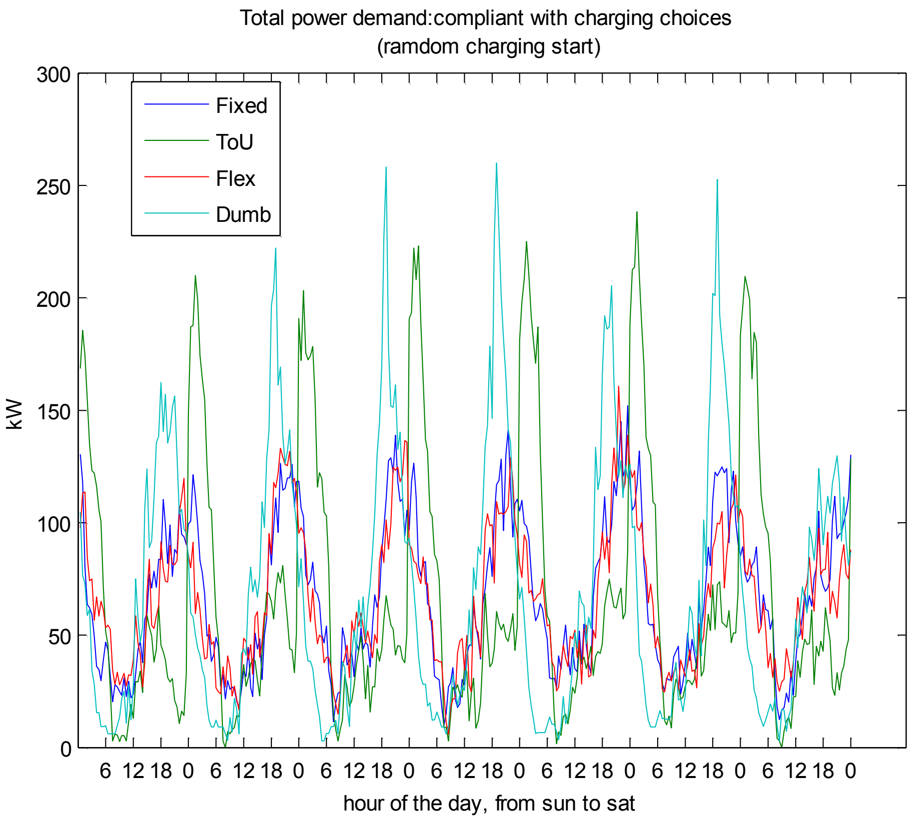

Figure 36: Power demand from home charging when charging start time is scattered randomly but compatibly with the charging choices

Indeed, the choice compliant load in the time-of-use pricing scenario, when the energy delivery is initiated at random times has a valley filling effect. This is highlighted in Figure 37, where the home charging load from the present simulation is plotted on top of the total London domestic load, after being scaled up to match a 40% EV penetration amongst London's household cars. Graph *a* shows the case in which, under the time-of-use tariff, charging is initiated as soon as possible, compatibly with charging choices, graph *b* clearly shows the effect when, in the same pricing scenario, the energy delivery is initiated at random times, within the constraints posed by individual drivers charging choices.

This simple application suggests that electric vehicle drivers' charging preferences are compatible with intelligent charging operations, allowing an improvement in the exploitation of grid's generation resources.

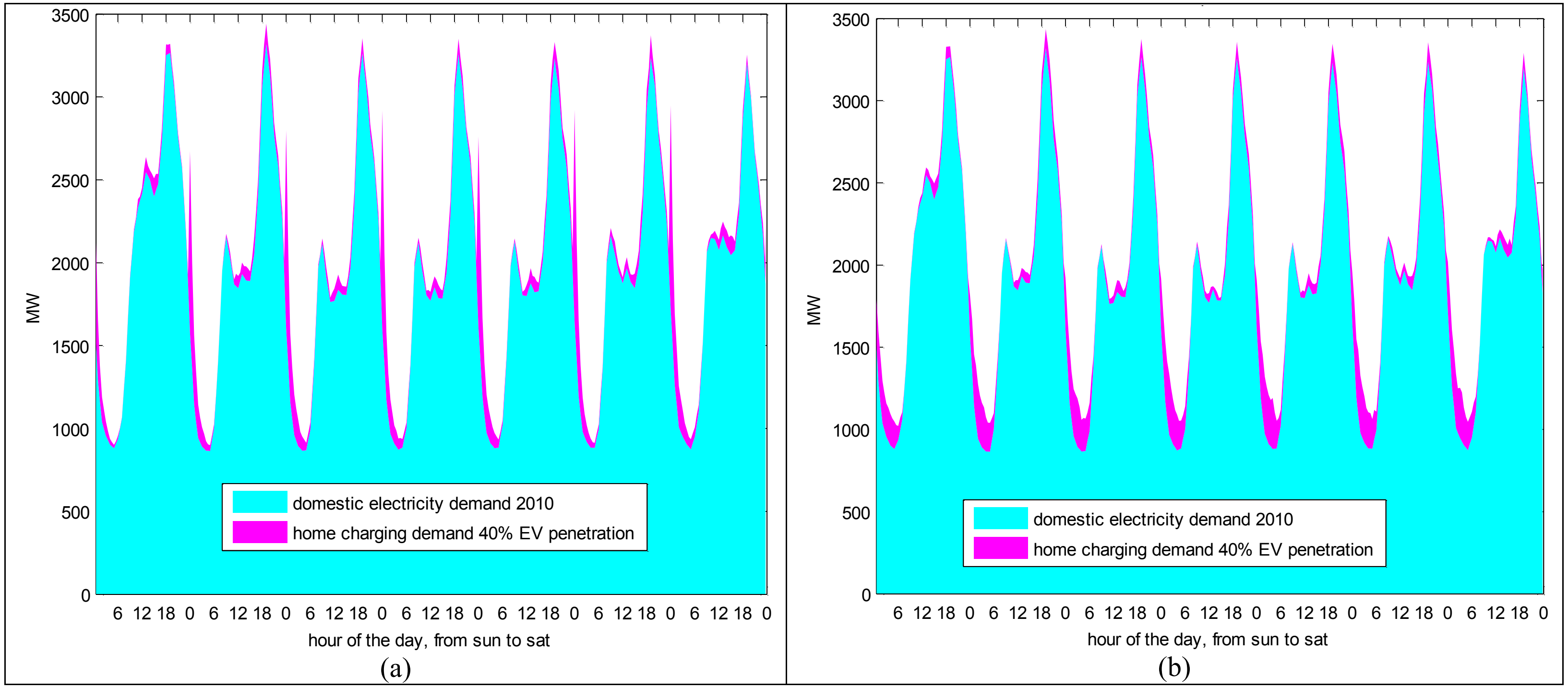

Figure 37: London domestic electricity demand and home charging demand[59] under the time-of-use pricing scenario. (a) Energy is delivered in the shortest possible time compatible with charging choices. (b) Energy is delivered scattering the charging start time randomly, compatibly with charging choices

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[59] The domestic electricity demand in London 2010, corresponds to a winter week in 2010. The data was previously used by (Strbac et al., 2012), who kindly provided it to the author. The charging demand is obtained by scaling the demand from the 2010 NTS sample to 40% of the total number of car available to London households for private use in 2011, according to the 2011 census (ONS, 2012).These graphs thus do not represent a forecast, but should be considered as indicative of high EV penetration scenarios.

6.6 Summary and conclusion

This chapter has presented a demonstration application of the use of the charging choice framework developed in Chapter 3. The framework was implemented as a micro-simulation tool and utilised to analyse the flexibility of electric vehicle home charging load, implied by electric vehicle charging choices simulated for London vehicle patterns.

The simulation results have shown how charging choices imply a flexible load for all charging pricing scenarios considered. In all three price scenarios, in over 80% of the charging operations the CBCF was above 0.5. This means that for this large share of charging operations at least half of the chosen charging durations were above the minimum time strictly necessary to supply the energy amounts requested. In this 80% of cases, therefore, the charging service provider could supply the energy in at least twice as much time as it would take to charge the vehicle battery continuously at the nominal supply power of the charging equipment (3 kW, this case). The significance of the fact that flexibility is achieved in all pricing scenarios is that if electric vehicle users are enabled to make charging choices within a smart charging setting, allowing them to choose the energy that they want to charge and the time in which they want the charging operation to be finished, their choices imply load flexibility, even in fixed price scenarios. This suggests that the implementation of optimised charging profiles by charging service operators is feasible, even in the absence of monetary incentives aimed at fostering flexible load, provided that a choice enabling smart charging infrastructure is in place. For instance, under the assumptions of the simulation, considering the fixed price scenario, simply scattering the charging operations randomly start time, leads to a maximum peak in power that is 58% of the maximum peak that one observes in the uncontrolled charging scenario. Considering the ToU scenario and the same trivial supply criterion, this reduction is only 8%, but the peaks in charging demand are shifted to low domestic demand hours.

The analysis of choice based charging flexibility is an original contribution of this dissertation since, to the author's knowledge, this type of analysis has not previously been carried out in the literature.

6.6.1 Limitations

Simulation framework - the simulation framework developed focuses only on the demand side, neglecting supply side considerations that may be significant in large deployment scenarios. An important line for future work would be to extend the model to accommodate competition amongst EV users for potentially limited availability of charging posts or electricity distribution network capacity. It might be expected that competition for limited infrastructure availability may reduce CBCF, because the number of effective charging opportunities may be lower.

Simulation scenarios and assumptions - these include the EV and infrastructure characteristics. In this study only one EV type was simulated while, in practice, different battery sizes, consumption characteristics and stages of battery life, may each affect how fast a battery is depleted. These are all sources of variability in the charging options in the choice sets across different vehicles (i.e. they affect the available energy dimension of the charging choice space, shown in Figure 27). Likewise, having a single consumption level, independent of the actual tour characteristics (e.g. urban or extra urban or mixed), is a further source of variability affecting the available charging options at a given charging opportunity. Similarly, the power available for the charging equipment was fixed in this study, and this also affects the availability of charging options: fast charging, for example, if available at various charging opportunities, would increase the area of the choice space in Figure 27. The assumption mentioned, together with the infrastructure availability assumption, could be addressed by modifying the simulation settings to generate more complex and realistic scenarios than that used for this simple demonstration.

Disparity between choice mode estimation dataset and vehicle diaries in simulation - the dataset used to estimate the choice model used in the simulation is not representative of the London vehicle patterns simulation. For analyses of London charging demand with a scope beyond the model demonstration, empirical choice models estimated on more representative samples would be required.

Chapter 7
CONCLUSIONS

The contribution of electric vehicles (EV) to the diversification of the transport fuel mix is expected to lead to a reduction in oil dependence and therefore the enhancement of energy security of countries, like the UK, which traditionally rely heavily on foreign imports. Electrification of road transport, as the power sector is gradually decarbonised, will in the longer term also allow a progressive reduction in the sector's climate impact. Furthermore, the zero tailpipe emissions of EVs can help to reduce air pollution in cities in an increasingly urbanised world. Finally, the development of an EV supply chain has the potential to stimulate economic growth in countries engaging in this development. Governments around the world, therefore have been putting in place policies to reach high EV penetration targets within their national fleets.

The study of the potential impacts of electric vehicle deployment, as well as the challenges related to the integration of the road transport and national power systems, must rely on mathematical models. Amongst the challenges in modelling these integrated EV-power systems there is the necessity to model the response of drivers to demand management strategies aimed at reducing the impacts at various levels of the power network from EV charging load, as well as at exploiting the potential flexibility of such loads in order to enhance grid operations. In other words, such models need to account for the effect of consumer choices in the realisation of the so called "smart charging" of electric cars.

Improved models for electric vehicle use and charging behaviour also have the potential to improve the assessment of the benefit sought from road transport electrification.

7.1 Summary and conclusions

In thesis the role of consumers' behaviour into the integration of mobility and power systems is explored by developing a methodology to investigate electric vehicles (EV) charging choices in technological scenarios that enable smart charging operations.

A modelling framework for the joint analysis of EV charging and activity-travel behaviour is presented. This consists in an extension of traditional activity scheduling models that incorporated the charging choice dimensions. The framework developed captures tradeoffs between available energy, charging duration, and charging costs and well as electric vehicle use timing. This enables modelling the potential effects of charging service pricing and charging demand management policies on charging choices as well as along the timing dimension of travel/activity choices as a driver's response based on drivers' preferences. This essentially achieves the first objective of this thesis. The limitations of this modelling framework are summarised in subsection 7.3.1.

The development of stated response survey instrument, ECarSim, for estimating a tour-based operational version of the model is reported. The main data generation process in ECarSim is two choice experiments in which respondents choose between two charging options for the time their hypothetical electric car is parked at home before the next planned home based tours. The charging operation is assumed to be controlled by an external charging service provider. A charging option is characterised by the available energy levels at the end of the charging operation and the charging duration, and the cost. The main difference between the first and the second choice experiments, is that the second allows variation in the planned tour timing, since the charging operation duration may imply schedule delays.

Empirical results from the estimation of discrete choice models from the two separate choice experiments provide insights into the value placed by individuals on the main attributes of the charging choice (charging duration and available energy after charging). Estimates for the marginal utilities from the separate analyses of the two choice experiments in the ECarSim suggest a high heterogeneity in charging behaviour, that in part was captured by individual characteristics but in part remain unobserved. *Inter alia*, part of the heterogeneity was found to be associated to range anxiety, as this individual characteristics cannot be measured objectively it was modelled making use of an integrated choice and latent variable choice model. This empirical exploration of electric vehicle use scheduling and charging preferences essentially achieves the second objective of this thesis, within the limitations summarised in subsection 7.3.2.

Finally, a tour based model based on the modelling framework is estimated using jointly data from the two choice experiments of ECarSim. This empirical model is then implemented into a micro-simulation framework to demonstrate the model applicability for modelling electric vehicle charging demand. The specific application presented in this study shows the compatibility of charging choices under various electricity pricing scenarios with electric vehicle load flexibility – an essential requirement to enable smart charging operations. The simulation results have shown how charging choices imply flexible load under various pricing scenarios considered. The significance of this result that if electric vehicle users are enabled to make charging choices within a smart charging paradigm, which allows them to choose the energy that they want to charge and the time they want the charging operation to be finished, their choices imply load flexibility even in fixed price scenarios. Therefore implementation of optimised charging profiles by charging service operators appears to be feasible, even in absence of monetary incentives to drivers aimed at fostering flexible load, provided that a choice enabling charging infrastructure is in place. Thus this simulation finally achieves the third objective of this thesis, within the limitations summarised in subsection 7.3.2.

7.2 Thesis contributions

The contributions that this research has made are summarised below:

- Formalisation of the charging choice attributes that transcend the operational charging regime, and that can be applied to express charging preferences in both traditional or smart charging;
- The development of a modelling framework explicitly considering charging choice as an additional dimension of travel choices that involve electric vehicle use;
- The development of choice experiments for the analysis of charging preferences in smart charging operation scenarios;
- The exploratory analysis of the preferences above amongst car owning drivers;
- The development of an approach to analyse the extent to which individual preferences allow electric vehicle load flexibility, i.e. effectively enable smart charging operations.

As part of this study, the following scholarly articles were prepared:

1. Daina, N., Sivakumar, A. & Polak, J. W. (2011). The valuation of low carbon vehicle attributes amongst potential early adopters. Paper presented at the Universities' Transport Study Group Conference, Milton Keynes.

2. Daina, N., Sivakumar, A. & Polak, J. W. (2012). Development of a Stated Response Survey for Electric Vehicle's Users Charging and Mobility. Paper presented at the Universities' Transport Study Group Conference, Aberdeen.
3. Daina, N., Sivakumar, A. & Polak, J. (2012). A framework for joint analyses of electric vehicle use and charging. Paper presented at the 13th International Conference on Travel Behaviour, Toronto.
4. Daina, N. (2013). Electric vehicle market: stated valuation of the charging operation. Paper presented at the Universities' Transport Study Group Conference, Oxford.
5. Daina, N., Sivakumar, A. & Polak, J. (2013). Modelling the Effects of Range Uncertainty on Electric Vehicle Users' Charging Behaviour. Paper presented at the International Choice Modelling Conference 2013 Sydney.
6. Daina, N., Sivakumar, A. & Polak, J. W. (2014). Empirically grounded electro-mobility micro-simulations in smart grid contexts. Paper presented at the Universities' Transport Study Group Conference, Newcastle.

7.3 Limitations and future work

7.3.1 Modelling framework

The first limitation is that only the timing dimension of EV travel is considered to be affected by charging choices whereas, as argued in Chapter 3, other dimensions of travel are intrinsically linked with charging choices. A way to move beyond this limitation without substantially changing the structure of the current model, would be to integrate it within activity-based travel demand modelling systems, similar to what is done in the PMPSS-MATSim model system discussed in Chapter 2. This would be an essential step in future work intended to enable more comprehensive analyses of the impacts of charging demand management strategies on travel patterns defined more broadly than just the travel timing.

The second limitation of the framework is the intrinsically myopic behaviour implied by considering charging choices as occurring independently from each other at each charging opportunity. This limitation is the result of the fact that the EV driver is assumed to use information only about the current charging opportunity and the travel episode occurring just after. A dynamic choice module would be necessary to overcome this limitation. The EV driver would need to maximise their utility over a longer time horizon potentially including multiple charging opportunities. This would entail assuming the capability of the EV driver (i.e. the electric vehicle driver) to solve a dynamic programming problem, which may be farfetched. Nevertheless, a dynamic choice model formulation appears a particularly important future development to pursue, especially in order to model charging choices in complex time of day electricity pricing regimes.

7.3.2 Charging behaviour analyses and model application

The main limitation of the empirical results presented in Chapter 5 is that they are not readily generalised to the entire population of drivers in the UK (or even in London) since it was not possible to collect a representative dataset within the confines of this study. Notwithstanding, the present results provides useful insight into charging behaviour that could be deployed to improve and extend the data collection.

The limitation mentioned above obviously extends to the simulation in chapter 6. Clearly such a limitation does not allow drawing general conclusions about London home charging demand. The main purpose of the chapter was, however, to demonstrate the potential of the model. In order to actually model charging demand in the London area, representative data on charging choices needs to be collected and the charging choice model re-estimated.

The use of revealed preference data jointly with choice experiment data is also recommended for future estimations of the model. Furthermore, the external validity of the model could in turn be tested using part of the revealed preference dataset for cross validation.

Moreover the model implementation for policy analysis can be improved by a more complete representation of the activity-travel related portion of the utility functions, of the charging and activity-travel alternatives: first by relaxing the assumption of constant travel times throughout the day, second by considering alternative to electric vehicle use in a more complex way than just by making use of alternative specific constant for charging mode or avoid travelling. As mentioned in the previous subsection a thorough treatment of the travel dimensions could be achieved with the integration of the current model within an activity-based model for travel analyses. An intermediate step could be the integration of the charging choice, a mode and time of day choice, i.e. to extend the current model to methodically include the mode choice.

The simulation framework neglects the effect of possible supply side issue such as competition amongst EV drivers for charging infrastructure as well as electric network capacity. These effects may be important in contexts of large EV penetration and need to be addressed in the future. The second in particular requires integrations of EV use and charging demand simulation model with a power system models.

The simulation results presented are also affected by the simple scenarios adopted in terms full EV penetration, of EV characteristics and charging infrastructure availability. While these scenarios were chosen for demonstrative purposes, the simulation tool allows the representation of more complex and possibly realistic scenarios, which can be explored in future applications.

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Appendix A - Investigation of systematic heterogeneity in SCE1

The specification of systematic heterogeneity in charging attributes in Table 17 was obtained through following this process.

- One model (model A) was estimated by including interactions between only the individual characteristics shown in Table 11 together with available energy, charging duration and charging cost.
- One model (model B) was estimated by including interactions between only the tour characteristics shown in Table 11 and available energy and charging duration.
- The model in Table 17 was obtained by adding to the base specification only those variables in models A and B which were found to be significant with a 80% level of confidence.

Despite its significance, the interaction between charging duration and employment status in model A was excluded because it leads to a positive value for the charging duration parameters for individuals in employment. For the same reason the significant interaction term between charging duration and work tour purpose, specified in model B, was excluded from the final model. Excluding significant but non-essential terms from model specification because of their "wrong" sign is customary during specification searches (Ortuzar and Willumsen, 2011).

Model A	Value	Std err	t-test	p-value	Keep in final model?
A	0	fixed			
B	-0.00683	0.0764	-0.09	0.93	
CC	-0.515	0.201	-2.56	0.01	keep
CC*Employed	0.239	0.157	1.52	0.13	keep
CC*Female	-0.0753	0.0949	-0.79	0.43	reject
CC*No university	0.105	0.114	0.93	0.35	reject
CC*Age 20-35	-0.222	0.152	-1.47	0.14	keep
CC*Age 36-55	-0.0659	0.153	-0.43	0.67	reject
CC*Age 56+	0	fixed			
FFC	1.12	0.221	5.05	0	keep
FFC* NACS	-3.55	0.272	-13.04	0	keep
E	0.179	0.0746	2.4	0.02	keep
E*Employed	0.0126	0.0626	0.2	0.84	reject
E*Female	-0.0626	0.0357	-1.75	0.08	keep
E*No university	-0.0371	0.0413	-0.9	0.37	reject
E*Age 20-35	-0.0174	0.0615	-0.28	0.78	reject
E*Age 36-55	0.0754	0.0631	1.19	0.23	reject
E*Age 36-55	0	fixed			
CT	-0.489	0.342	-1.43	0.15	keep
CT *Employed	0.593	0.315	1.89	0.06	reject
CT *Female	0.0212	0.127	0.17	0.87	reject
CT *No university	-0.453	0.147	-3.07	0	keep
CT *Age 20-35	-0.0548	0.224	-0.24	0.81	reject
CT *Age 36-55	-0.185	0.23	-0.8	0.42	reject
CT *Age 36-55	0	fixed			
Number of estimated parameters	21				
Number of observations	1056				
Number of individuals	1056				
Null log-likelihood	-731.963				
Final log-likelihood	-540.662				
Rho-square	0.261				
Adjusted rho-square	0.233				

Model B	Value	Std err	t-test	p-value	Keep in final model?
A	0	fixed			
B	-0.0202	0.0788	-0.26	0.8	keep
CC	-0.466	0.0509	-9.16	0	keep
FFC	-0.169	0.251	-0.67	0.5	keep
FFC*NACS	-1.76	0.303	-5.81	0	keep
CC	0.142	0.038	3.74	0	keep
E*Education tour purpose	-0.0283	0.0678	-0.42	0.68	reject
E*Leisure/social tour purpose	-0.0681	0.0397	-1.72	0.09	keep
E*Work tour purpose	-0.00292	0.0386	-0.08	0.94	reject
E*Distance 30-40miles	0	fixed			
E*Distance 41-50miles	0.273	0.0386	7.08	0	keep
E*Distance 51-60miles	0.354	0.0497	7.11	0	keep
E*Distance 61+miles	0.466	0.0847	5.5	0	keep
CT	-0.199	0.146	-1.36	0.17	keep
CT*Education tour purpose	0.72	0.651	1.11	0.27	reject
CT*Leisure/social tour purpose	-0.0822	0.159	-0.52	0.61	reject
CT*Work tour purpose	0.545	0.192	2.84	0	reject
CT*Peak time travel	-0.588	0.159	-3.7	0	keep
Number of estimated parameters	16				
Number of observations	1056				
Number of individuals	1056				
Null log-likelihood	-731.963				
Cte log-likelihood	-729.9				
Init log-likelihood	-731.963				
Final log-likelihood	-516.618				
Likelihood ratio test	430.69				
Rho-square	0.294				
Adjusted rho-square	0.272				

Appendix B - Stability of ICLV parameters

Table 29: ICLV empirical identification analysis – stability of model parameters with increasing number of draws and varying starting points of maximum simulated likelihood estimation

Runs	Run1	Run2	Run3	Run4	Run5	Run6	Run7	Run8
N of draws	500	1000	1000	1000	1000	1000	5000	10000
N of parameters	10	10	10	10	10	10	10	10
N of respondents	88	88	88	88	88	88	88	88
N of observations	755	755	755	755	755	755	755	755
Overall model log-likelihood	-336.881	-337.128	-337.194	-336.693	-336.054	-337.900	-336.947	-336.750
Choice model null log-likelihood	-523.326	-523.326	-523.326	-523.326	-523.326	-523.326	-523.326	-523.326
Choice model final log-likelihood	-370.506	-370.501	-370.657	-370.462	-369.679	-371.472	-370.569	-370.352
Choice model adjusted rho	0.273	0.273	0.273	0.273	0.274	0.271	0.273	0.273
Parameters								
$\gamma_{Age\ 36+}$	-0.490	-0.496	-0.562	-0.517	-0.568	-0.505	-0.529	-0.523
γ_{Female}	-0.246	-0.281	-0.303	-0.263	-0.234	-0.276	-0.289	-0.284
$\gamma_{Employed}$	0.436	0.441	0.450	0.403	0.436	0.415	0.439	0.432
σ_{ω}	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)
θ	0.051	0.050	0.050	0.052	0.051	0.052	0.051	0.051
σ_{ϵ}	0.163	0.163	0.163	0.162	0.163	0.163	0.163	0.163
A	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)
B	-0.036	-0.037	-0.037	-0.035	-0.035	-0.036	-0.036	-0.036
β_E	0.413	0.425	0.433	0.427	0.430	0.426	0.429	0.430
β_{CT}	-0.417	-0.421	-0.418	-0.419	-0.420	-0.417	-0.419	-0.419
β_{CC}	-0.670	-0.674	-0.673	-0.675	-0.677	-0.672	-0.673	-0.674
β_{X^*E}	0.367	0.381	0.374	0.378	0.374	0.379	0.372	0.375
t-stats								
$\gamma_{Age\ 36+}$	-1.977	-2.172	-2.307	-2.241	-2.481	-2.178	-2.205	-2.235
γ_{Female}	-1.003	-1.217	-1.239	-1.129	-0.999	-1.167	-1.186	-1.207
$\gamma_{Employed}$	1.821	1.982	1.904	1.782	1.937	1.820	1.870	1.891
σ_{ω}	***	***	***	***	***	***	***	***
θ	2.607	2.507	2.544	2.679	2.626	2.601	2.618	2.614
σ_{ϵ}	12.730	12.760	12.727	-12.693	-12.702	-12.705	12.700	-12.707
A	***	***	***	***	***	***	***	***
B	-0.344	-0.345	-0.344	-0.332	-0.328	-0.342	-0.337	-0.341
β_E	4.541	4.534	4.560	4.608	4.629	4.577	4.541	4.665
β_{CT}	-4.309	-4.333	-4.307	-4.310	-4.328	-4.306	-4.320	-4.318
β_{CC}	-8.605	-8.617	-8.617	-8.621	-8.636	-8.599	-8.615	-8.619
β_{X^*E}	7.272	7.519	7.451	7.566	7.742	7.386	7.525	7.551

Table 30: ICLV empirical identification analysis – retrieval of model parameters from synthetic data

	Original parameters	**Parameters retrieved from synthetic data**										
N of draws	10000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
N of parameters	10	10	10	10	10	10	10	10	10	10	10	10
N of respondents	88	88	88	88	88	88	88	88	88	88	88	880
N of observations	755	755	755	755	755	755	755	755	755	755	755	7550
Overall model log-likelihood	-336.750	-308.695	-305.660	-329.621	-302.148	-280.435	-294.714	-331.887	-261.714	-318.599	-302.212	-3233.778
Choice model null log-likelihood	-523.326	-523.326	-523.326	-523.326	-523.326	-523.326	-523.326	-523.326	-523.326	-523.326	-523.326	-5233.261
Choice model final log-likelihood	-370.352	-349.837	-339.726	-370.160	-342.117	-310.353	-333.460	-366.160	-318.058	-351.994	-336.096	-3562.350
Choice model adjusted rho	0.273	0.312	0.332	0.274	0.327	0.388	0.344	0.281	0.373	0.308	0.339	0.317
Parameters												
$\gamma_{Age\ 36+}$	-0.523	-0.609	-0.824	-0.426	-0.502	-0.421	-0.573	-0.526	-0.438	-0.452	-0.232	-0.488
γ_{Female}	-0.284	0.069	-0.098	-0.086	-0.643	-0.159	0.126	-0.486	-0.859	-0.558	0.071	-0.255
$\gamma_{Employed}$	0.432	0.287	0.734	0.763	0.244	0.284	0.481	0.625	0.636	0.596	0.460	0.335
σ_{ω}	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)
θ	0.051	0.047	0.046	0.020	0.059	0.058	0.072	0.039	0.026	0.044	0.036	0.052
σ_{ϵ}	0.163	0.150	0.163	0.152	0.151	0.170	0.152	0.163	0.127	0.164	0.164	0.164
A	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)
B	-0.036	-0.072	-0.173	-0.114	-0.030	0.006	-0.168	0.031	-0.223	-0.048	0.014	-0.061
β_{E}	0.430	0.448	0.387	0.271	0.521	0.535	0.391	0.394	0.501	0.401	0.329	0.426
β_{CT}	-0.419	-0.412	-0.386	-0.192	-0.390	-0.557	-0.451	-0.365	-0.420	-0.398	-0.313	-0.396
β_{CC}	-0.674	-0.676	-0.687	-0.532	-0.618	-0.720	-0.759	-0.643	-0.598	-0.753	-0.649	-0.661
β_{X^*E}	0.375	0.343	0.348	0.305	0.406	0.469	0.378	0.299	0.485	0.314	0.399	0.359
St-errors												
$\gamma_{Age\ 36+}$	-2.235	0.242	0.245	0.256	0.227	0.246	0.229	0.250	0.248	0.240	0.244	0.075
γ_{Female}	-1.207	0.246	0.242	0.264	0.236	0.256	0.229	0.253	0.252	0.246	0.254	0.076
$\gamma_{Employed}$	1.891	0.236	0.242	0.272	0.222	0.240	0.218	0.250	0.258	0.253	0.262	0.074
σ_{ω}	***	***	***	***	***	***	***	***	***	***	***	***
θ	2.614	0.018	0.017	0.017	0.017	0.022	0.018	0.018	0.013	0.019	0.020	0.006
σ_{ϵ}	-12.707	0.012	0.013	0.012	0.012	0.014	0.012	0.013	0.010	0.013	0.013	0.004
A	***	***	***	***	***	***	***	***	***	***	***	***
B	-0.341	0.108	0.111	0.103	0.111	0.120	0.112	0.104	0.118	0.107	0.113	0.034
β_{E}	4.665	0.086	0.087	0.093	0.097	0.122	0.077	0.082	0.140	0.084	0.113	0.028
β_{CT}	-4.318	0.101	0.094	0.089	0.099	0.108	0.098	0.091	0.105	0.094	0.094	0.030
β_{CC}	-8.619	0.074	0.077	0.067	0.076	0.085	0.079	0.072	0.080	0.076	0.078	0.024
β_{X^*E}	7.551	0.046	0.047	0.041	0.053	0.067	0.050	0.043	0.067	0.042	0.053	0.015

Appendix C - estimation of discrete choice models from multiple data sources

This Appendix describes in more detail the methodology for estimating discrete choice models from multiple data sources. Since the discrete choice modelling literature mainly focuses on estimation using jointly revealed preference (RP) data and stated preference (SP) data, the same is done here. The methodology can be extended, however, for joint estimation using, for example, multiple SP datasets.

The potential

The use of multiple data sources for model estimation is adopted in order to exploit the potential for synergy. This is particularly obvious in the joint use of RP and SR data. In fact, RP data is characterised by an intrinsic validity since it represents what happens in the real world. This data source is particularly suited for modelling short-term departures from a current state of affairs. On the other hand, this is less powerful for modelling situations in which changes from the current state are larger. In the latter case, stated response data is more effective; in fact, a stated response survey allows the collection of data about scenarios that new to respondents. Also, stated response surveys in the form of stated preference (SP) tasks, can provide more trade-off information and can be designed so that estimated models are more robust than models estimated from RP data (Louviere et al., 2000). On the other hand, SR data has the drawback that it is subject to the biases that arise when a respondent is asked to choose based on hypothetical situations. The *data enrichment* process constituted by pooling SR and RP data, and then estimating a model from the assembled data, can allow the strengths of the two sources to be exploited while mitigating their respective weaknesses (Louviere et al., 2000).

Data enrichment paradigms

Louviere et al. (2000) indentify two main paradigms of synergistic use of SP-RP data in choice modelling, the first is the proper data enrichment paradigm (Figure 38). In this view the objective of the analyst is to generate a model able to predict “real future market scenarios”. For this goal the analyst collects RP data containing equilibrium and trade-off information in a real market. However trade-off information maybe deficient, therefore SP data are collected, from the same or a different sample. In this paradigm from the SP data only attribute trade-offs information is used, that is pooled with RP information to produce the final model. In the second paradigm (Figure 39) from each data set only the information for which is superior to the other is used, disregarding the rest, e.g. SP used to capture the trade offs (i.e. the relative values attribute coefficients), while the RP data the market equilibrium (i.e. the alternative specific constants).

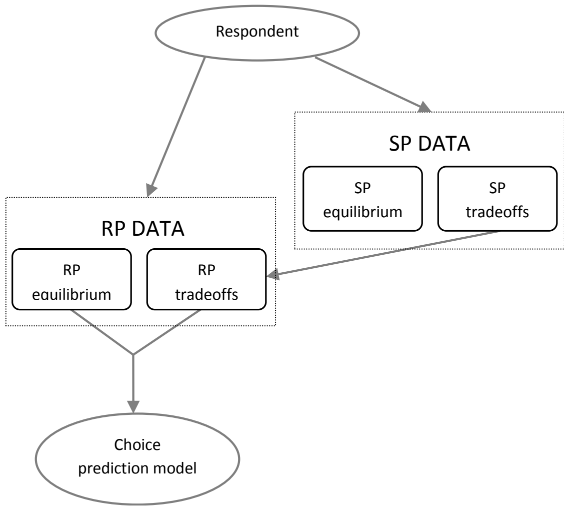

Figure 38: Data enrichment paradigm 1 (Louviere et al., 2000).

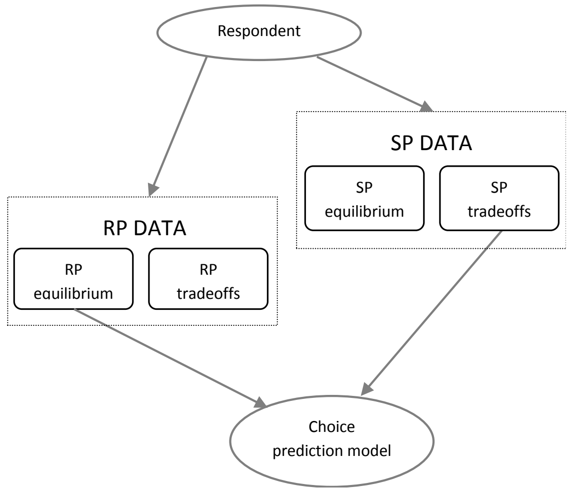

Figure 39: Data enrichment paradigm 2 (Louviere et al., 2000).

The data pooling process

In general, the data pooling process assumes that the behavioural framework underlying the choice process is the same for both choices in the real market and choices in hypothetical situations. Random Utility Theory represents the most widely use behavioural framework to model discrete choices and, as previously mentioned in this thesis, is the theoretical framework utilised to model mobility and charging behaviour of electric vehicle users in this work. We therefore assume that revealed mobility and charging patterns in the current market situations, and the choice outcomes in the hypothetical situations, are the result of the same behavioural framework.

Although the RUM framework "is applicable for both RP and SP data", "the definition of the observed and unobserved influences on the choice outcome however varies" (Hensher and Bradley, 1993)(Hensher and Bradley, 1993) . Once the observed influence is accommodated in the functional specification of the systematic utility, the unobserved portion of the utility is unlikely to have the same distribution profile for the RP and SP datasets. In particular, as "the RP and SP choice settings are quite different, there is no reason to believe that the variance of the unobserved factors in the RP setting will be identical to that of the variance of unobserved factors in the SP setting" (Bhat and Castelar, 2002). The issue has been recognised and a solution proposed first by Morikawa (1989), who suggested rescaling the variance of the error term associated with SP data so that the equality with the variance of the RP data is established. The fundamental problem here is the identification of the scaling factor due to the well-known inseparability of taste and scale (Ben-Akiva and Lerman, 1985). Since Morikawa's seminal work, several solutions have been proposed to accommodate heteroskedasticity due to data from different sources, e.g. by Ben-Akiva and Morikawa (1991) and Swait and Louviere (1993). The approaches used in these works to identify the scaling factor have been adapted in order to make use of a nested logit full information maximum likelihood estimation as described by e.g. Hensher and Bradley (1993).

The scalability problem is not the only issue that should be accounted for in the joint analysis of revealed and stated preference data. Bhat and Castelar (2002) highlight further important issues to consider:

- Inter-alternative error structure,
- Unobserved heterogeneity effects,
- State-dependence effects and heterogeneity in the stated dependence.

These issues are not specific to joint SP and RP model estimation, instead they affect the choice situation which is being modelled. Bhat and Castelar (2002) argue that when estimating models using joint RP-SP data, while the scalability problem is usually accounted for, these other issues are often neglected, even though they may characterise the choice being modelled: they therefore propose a unified mixed logit framework that accommodates them all.

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Appendix D - Lookup tables for variables used in estimated models

Variables in specifications of models estimated in Chapter 5 for choice experiment 1

Variable name	Meaning and units
A	Dummy variable equal to one for charging option A, zero otherwise
B	Dummy variable equal to one for charging option B, zero otherwise
FFC	Dummy variable equal to one for full and fast charging options, (E=24kWh, CT=3hours) (see, subsection 5.3.4)
E	Available energy after charging in kWh
CC	Charging cost in £
CT	Charging duration in 10 hours
NACS	Dummy variable equal to one, when choice situation does not contain alternatives with ambiguity in tour feasibility (see, subsection4.8.1)
Education tour purpose	Dummy variable equal to one if tour after charging has an education activity as main purpose, zero otherwise
Leisure/Social tour purpose	Dummy variable equal to one if tour after charging has a leisure/social activity as main purpose, zero otherwise
Work tour purpose	Dummy variable equal to one if tour after charging has a work purpose as main purpose, zero otherwise
Distance 41-50 miles	Dummy variable equal to one if tour after charging has a length comprised between 41-50 miles, zero otherwise
Distance 51-60 miles	Dummy variable equal to one if tour after charging has a length comprised between 51-60 miles, zero otherwise
Distance 61+ miles	Dummy variable equal to one if tour after charging has a length comprised over 60 miles, zero otherwise
Travel in peak periods	Dummy variable equal to one if the outbound leg of the tour after charging occurs at least partially in periods 7-9am or 4-6pm
Employed	Dummy variable equal to one if driver is in employment either full or part time, zero otherwise
Female	Dummy variable equal to one if driver is a woman, zero otherwise
Age 20-35	Dummy variable equal to one if driver aged between 20 and 35 years old, zero otherwise
Age 36-55	Dummy variable equal to one if driver aged between 36 and 55 years old, zero otherwise
No university	Dummy variable equal to one if driver does NOT hold any of the following: • University Higher Degree (e.g. MSc; PhD), • First degree level qualification (e.g. BA; BSc; PGCE), • Diploma in higher education; HNC, HND, Nursing or Teaching qualification (excluding PGCE), • zero otherwise

Variables in specifications of models estimated in Chapter for choice experiment 2

Variable name	Meaning and units
A1, A2, A3, A4	Alternative specific constants for the activity curtaining options at destinations, for charging alternative A
B1, B2, B3, B4	Alternative specific constants for the activity curtaining options at destinations, for charging alternative B
EV	Dummy variable indicating an electric vehicle use and charging alternative
NT (no charging and no travel)	Dummy variable equal to one for the alternative: Avoid both charging strategies and do not travel
OM (no charging and travel with other mode)	Dummy variable equal to one for the alternative: Avoid both charging options and travel with other mode
E	Available energy after charging in kWh
CC	Charging cost in £
CISDL	Charging induced schedule delay in hours
DL	Dummy variable equal to one if there is a non-zero schedule delay, , zero otherwise
PD	Decrease in activity participation time in hours
Education tour purpose	Dummy variable equal to one if tour after charging has an education activity as main purpose, zero otherwise
Leisure/Social tour purpose	Dummy variable equal to one if tour after charging has a leisure/social activity as main purpose, zero otherwise
Work tour purpose	Dummy variable equal to one if tour after charging has a work purpose as main purpose, zero otherwise
Distance 41-50 miles	Dummy variable equal to one if tour after charging has a length comprised between 41-50 miles, zero otherwise
Distance 51-60 miles	Dummy variable equal to one if tour after charging has a length comprised between 51-60 miles, zero otherwise
Distance 61+ miles	Dummy variable equal to one if tour after charging has a length comprised over 60 miles, zero otherwise
Travel in peak periods	Dummy variable equal to one if the outbound leg of the tour after charging occurs at least partially in periods 7-9am or 4-6pm
Timing of travel not flexible	Dummy variable equal to one if tour after charging is not flexible in time
Employed	Dummy variable equal to one if driver is in employment either full or part time, zero otherwise
Female	Dummy variable equal to one if driver is a woman, zero otherwise
Age 20-35	Dummy variable equal to one if driver aged between 20 and 35 years old, zero otherwise
Age 36-55	Dummy variable equal to one if driver aged between 36 and 55 years old, zero otherwise
No university	Dummy variable equal to one if driver does NOT hold any of the following: • University Higher Degree (e.g. MSc; PhD), • First degree level qualification (e.g. BA; BSc; PGCE), • Diploma in higher education; HNC, HND, Nursing or Teaching qualification (excluding PGCE), • zero otherwise

Variables in specifications of the model estimated in Chapter 6 using data from choice experiement1 and choice experiment 2

Variable name	Meaning and units
A1, A2, A3, A4	Alternative specific constants for the activity curtailing options at destinations, for charging alternative A
B1, B2, B3, B4	Alternative specific constants for the activity curtailing options at destinations, for charging alternative B
A_SCE1	Dummy variable equal to one for charging option A, zero otherwise, in choice situation form choice experiment 1
B_SCE1	Dummy variable equal to one for charging option B, zero otherwise in choice situation form choice experiment 1
EV	Dummy variable indicating an electric vehicle use and charging alternative
NT (no charging and no travel)	Dummy variable equal to one for the alternative: Avoid both charging strategies and do not travel
OM (no charging and travel with other mode)	Dummy variable equal to one for the alternative: Avoid both charging options and travel with other mode
E	Available energy after charging in kWh
CC	Charging cost in £
CISDL	Charging induced schedule delay in hours
DL	Dummy variable equal to one if there is a non-zero schedule delay, , zero otherwise
PD	Decrease in activity participation time in hours
FFC	Dummy variable equal to one for full and fast charging options, (E=24kWh, CT=3hours) (see, subsection 5.3.4)
NACS	Dummy variable equal to one, when choice situation does not contain alternatives with ambiguity in tour feasibility (see, subsection4.8.1)
Distance	Distance of tour after charging in 100miles

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