# Electric vehicle charging choices: Modelling and implications for smart charging services

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A B S T R A C T

The rollout of electric vehicles (EV) occurring in parallel with the decarbonisation of the power sector can bring uncontested environmental benefits, in terms of $CO_2$ emission reduction and air quality. This roll out, however, poses challenges to power systems, as additional power demand is injected in context of increasingly volatile supply from renewable energy sources. Smart EV charging services can provide a solution to such challenges. The development of effective smart charging services requires evaluating pre-emptively EV drivers' response. The current practice in the appraisal of smart charging strategies largely relies on simplistic or theoretical representation of drivers' charging and travel behaviour. We propose a random utility model for joint EV drivers' activity-travel scheduling and charging choices. Our model easily integrates in activity-based demand modelling systems for the analyses of integrated transport and energy systems. However, unlike previous charging behaviour models used in integrated transport and energy system analyses, our model empirically captures the behavioural nuances of tactical charging choices in smart grid context, using empirically estimated charging preferences. We present model estimation results that provide insights into the value placed by individuals on the main attributes of the charging choice and draw implications charging service providers.

## 1. Introduction

### 1.1. Context

In a context of a progressively decarbonised power sector, electric vehicles (EV) can bring significant reductions in $CO_2$ emissions from road traffic (IEA, 2009). Moreover, EVs' roll out improves air quality in urban areas.

However, EVs bring both challenges and opportunities for power systems. Amongst the challenges that large EV penetration may bring there is the potential increase of peak power demand if charging operations occur in coincidence of current demand peaks. Amongst the opportunities there is the possibility to use EV as flexible loads that can provide balancing services to grids with large shares of intermittent or fluctuating renewable energy generation (Kempton and Letendre, 1997; Kempton and Tomić, 2005). In order to fully exploit the potential of EVs as a flexible load smart charging strategies need to be implemented.

Smart charging can occur in a centralised way via aggregators or through decentralised control architectures (Galus et al., 2012). In the centralised framework EV owners do not have transactions in electricity markets, because of the low power of a

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single transaction (Bessa and Matos, 2012). In this centralised framework EV load aggregators act as an intermediary between vehicle owners and grid markets and contract power demand from several EVs. In the decentralised framework, individual EVs respond to market information made available to them. Typically, a static or dynamic price signal is used to incentivise a particular charging behaviour (Galus et al., 2012). An example of a static price signal is time-of-use tariffs that would incentivise charging overnight, similar to current time-of-use domestic tariffs for electricity.

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., 2012). Such actions must, however, respect the constraints imposed by owners' travel needs. Thus 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 energy requirement specifies the battery level required by the end of the charging operation while the timing requirement specifies the time by which the charging operation must be completed.

Under this scheme, users directly affect the flexibility of the controls that can be imposed on the charging operation through their charging preferences. Therefore it is in the interest of the operator to incentivise charging preferences that allow for more flexible operation. Contracts regulating the service provision could include the option for users to override the control imposed by the aggregator.

However, even in a decentralised framework, a central entity might provide these pricing signals to owners of electric vehicles (Galus et al., 2012). From this perspective, the centralised and the decentralised frameworks overlap.

### 1.2. Contributions

Despite the importance of users' behaviour in the context described, current smart charging strategies largely rely on simplistic or theoretical representation of EV charging and travel behaviour. The main contribution of this paper is a charging behaviour model that bridges the gap between the representations of charging behaviour used in integrated transport and energy system analyses for the appraisal of smart charging strategies, and the representations used in charging behaviour studies.

In integrated transport and energy system analyses, charging behaviour is represented either through charging behaviour scenarios (Koyanagi and Uriu, 1997; Kang and Recker, 2009; Axsen and Kurani, 2010; Mullan et al., 2011; Weiller, 2011; Dong et al., 2014) or theoretical models (Waraich et al., 2009). The former are not policy sensitive and thus are not suitable for assessing the response of EV drivers' to smart charging services. The latter are policy sensitive, but they are not estimated empirically. The absence of strong empirical foundations may lead to weak behavioural realism of the responses to smart charging services.

Empirical evidence from charging behaviour literature shows that charging behaviour is heterogeneous amongst drivers (Franke and Krems, 2013; Zoepf et al., 2013). Such heterogeneity is related to differences in driving patterns, individual attitudes towards risk in dealing with limited range vehicles, and idiosyncratic preferences (Franke and Krems, 2013; Zoepf et al., 2013). However, the charging behaviour literature does not provide operational models of charging behaviour that can be used to analyse driver's response to smart charging services, because the response of drivers to pricing of charging services in smart grid contexts has yet to be addressed.

In the present work we develop a random utility model for charging behaviour that is empirically estimated using discrete choice analysis. Because we model jointly activity-travel scheduling choices and charging choices under the activity-based demand modelling paradigm, our charging behaviour model is well suited to be implemented as a module in integrated transport and energy model systems. However, unlike previous charging behaviour models applied in such model systems, ours captures the behavioural nuances of tactical charging choices in smart grid context. It can do so because the trade-offs involved in tactical charging choices in smart charging contexts are captured empirically by model estimation using discrete charging choice experiment data. Our discrete choice experiment were specifically designed to elicit drivers' charging preferences in smart charging contexts

In addition, another significant contribution is the introduction of the concept of *effective charging time* (ECT) as a dimension of charging choice. The definition of ECT (see next section) makes it possible to use the same representation of charging choice independent from the charging service under analysis.

### 1.3. Literature review

#### 1.3.1. Approaches for the appraisal of smart charging strategies

As, Daina et al. (2017) point out in a recent review, by and large the current practice for the appraisal of smart charging strategies assumes predefined charging scenarios and exogenous EV use patterns (Koyanagi and Uriu, 1997; Kang and Recker, 2009; Axsen and Kurani, 2010; Mullan et al., 2011; Weiller, 2011; Dong et al., 2014).

The use of predefined charging scenarios prevents analyses that are sensitive to electricity pricing, because the charging behaviour is set using rules. It also limits the representation of users' behaviour heterogeneity. The reliance on exogenous travel patterns implies that travel patterns are independent from the charging decisions. However, if individuals are flexible in their travel choices, ruling out an interdependence between travel and charging choices may lead to biased estimates of EV

use. Moreover, treating EV driving patterns as exogenous inhibits representing potentially relevant interactions (disruptive or synergistic) between time-of-use electricity pricing and road pricing policies.[1]

Exceptions to the use of charging behaviour scenarios and exogenous travel patterns are less common, but do exist (2017). Two related works by Galus and Andersson (2008) and Waraich et al. (2009) use agent based modelling and micro-simulation for plug-in hybrid electric vehicles (PHEV) use and charging modelling. These works, integrates the transport simulation environment MATSim, with a power system simulator. The integration occurs via a charging behaviour module sensitive to electricity pricing. The electricity price signal, generated by the power system module, affects PHEVs agent simulated decisions to drive and charge in MATSim. MATSim using an evolutionary algorithm modifies the driving and charging schedules of all PHEVs in the simulation attempting to increase the utility of each agent at each simulation step. Although the charging behaviour model adopted is coherent with a game-theoretical framework, allowing the modelled PHEV agents to compete for limited electric network capacity, it lacks a strong empirical foundation.

Kang and Recker (2014) apply Recker's (1995) Household Activity Pattern Problem framework (HAPP) to enable changes in travel-activity patterns caused by charging patterns. However, they use charging behaviour scenarios to define charging patterns.

Other models that take into account the effect of electric vehicle use on EV driver's activity-travel patterns include a study of vehicle to grid-operations using activity-based equilibrium scheduling (Nourinejad et al., 2016) and a study on intra-household interactions when scheduling EV use in households with multiple vehicles (Khayati and Kang, 2015). These two studies account for the interaction of EV use decisions and activity travel scheduling decisions in different ways. Nourinejad et al. (2016) adopt and extend Lam and Yin's (2001) time-based utility theory model, which does not treat schedule constraints explicitly but models the utility of an activity as time dependent and expresses the scheduling problem as a continuous equilibrium problem. Khayati and Kang (2015) use the Recker's (1995) Household Activity Pattern Problem framework (HAPP), in which the disutility of travel is minimised under spatial and temporal constraints. In the studies above, the effect of limited range of EV is accounted for, as a spatial constraint that excludes infeasible trip chains from a driver's choice set. In an analogous manner, limited range availability has also been treated as spatial constraints in traffic assignment models applied to electric vehicles (Wang et al., 2016). However, to define distance constraints, range levels needs to be observable. Instead, the range levels perceived by EV drivers are latent (Franke et al., 2012; Franke and Krems, 2013). Perceived range levels only partially indicated by the available energy stored in the vehicle battery. This poses a limitation in approaches that represent the effect of limited range in EV travel and charging decisions purely as spatial constraint.

The dominant tendency to rely on charging scenarios and exogenous travel patterns is a likely result of the dearth of data on EV charging and use from which to estimate empirical models. Revealed preference (RP) data about EV use and charging are difficult to access. Data generated in settings with variability in prices and tariff structures for charging services are still limited.

In order to analyse the response to charging service pricing, it is necessary to rely on choice experiment data, where hypothetical choice situations are presented to a sample of drivers. These "stated response" (SR) experiments offer the opportunity to collect "stated preference" data when preferences cannot be "revealed" in real world markets. SR tools are powerful in non-market situations but unavoidably carry biases inherent with hypothetical choice situations (Louviere et al., 2000).

### 1.3.2. Charging behaviour studies

While much effort has been devoted to describing aggregate spatiotemporal charging demand patterns (Westermann et al., 2010; Schey et al., 2012; Everett et al., 2011; Robinson et al., 2013) only few studies have focused on gaining insights on the factors driving charging behaviour (Franke and Krems, 2013; Zoepf et al., 2013; Yang et al., 2016). However, understanding individual behaviour is necessary for developing models to assess how an EV driver may respond to charging service propositions with varied characteristics.

Franke and Krems (2013) analysed the charging behaviour of participants in a German EV trial. As one would expect, they found strong evidence that range level affects charging decisions. Moreover, they discovered a significant heterogeneity in the range levels participant feel confortable with while driving their EVs. We submit that varying degrees of comfortable range can be represented in terms of heterogeneous preferences for range levels. This heterogeneity in preference can be explained by a number of factors which we will explore in later in this a paper. Franke and Krems provide compelling evidence of the behaviour mechanisms potentially underlying charging behaviour, but the theoretical framework they adopt to describe them, drawn from control theory and behaviour self-regulation, is difficult to operationalise.

Zoepf et al. (2013) used a random coefficients mixed logit model to model the occurrence of a charging operation at the end of PHEV journeys. The authors identified 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. The authors also found a significant standard deviation in most of the utility coefficients, bringing additional evidence for heterogeneity in charging preferences. While Zoepf

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[1] He et al. (2013) propose an analysis of integrated road and electricity pricing for electric vehicles in a scenario of wireless charging deployment, but it is a system level study, not providing insights on the users' response to such a regime, thus only marginally relevant here.

et al.'s model can be used for forecasting the occurrence of charging events, it is not, however, suited to model the behavioural response to tariff structures for charging services, because is not price sensitive.

More recently, Yang et al. (2016), brought further evidence, analysing data from stated choice experiments of the importance of state of charge levels (i.e. range levels) in charging decisions. Yang et al.'s work is also interesting because it address the study of charging choices contextually with route choice. This highlights the importance of considering the charging choice as further dimension of travel choices.

The study of charging choices in contexts where smart charging options are available deserves further investigation. To date behavioural studies around smart charging propositions have mainly focused on acceptance of smart charging services rather than trying to assess the users charging behaviour response (Bailey and Axsen, 2015; Will and Schuller, 2016). A notable exception is a study by Latinopoulos et al. (2017) who study the risky choice in early reservation of dynamically priced charging and parking services.

## 2. Modelling charging choices in smart charging contexts

### 2.1. Conceptual framework

Our aim is to model charging behaviour within the context of smart charging services. In order to achieve this aim we require an operational definition of charging choice, bridging the perspectives of EV drivers and the charging service provider (CSP).

Let us consider the drivers' perspective first. EV drivers are interested in the amount of energy stored in the vehicle's battery at any time. The amount of energy stored in the battery defines the spatial constraints of EV vehicle use. The time dimension is important as it determines *when* EV drivers can reach certain destinations to carry out their activities. The charging operation varies the amount of energy stored as a function of time. The duration of a charging operation depends on the vehicle and charger characteristics and on the charging strategy adopted by the supplier (in agreement with the driver). We thus define charging choice as the decision made by driver, at a given charging opportunity, to charge their vehicle to a specific charge level, starting from a specific instant, and to be made available by a certain time. This definition assumes that the driver has multiple charging options that are characterised by different battery levels at the end of the charging operation and different charging durations. These options might vary in price depending on pricing policies imposed by the CSP.

In turn, the CSP is interested in the time profile of power drawn by the EV is supplying when charging. This time profile is called charging profile or charging schedule. In a centralised framework, the CSP defines the charging profile within the constraints determined by the following three pieces of information (Sundstrom and Binding, 2011):

- The instant the vehicle is connected to the grid;
- The instant the vehicle must be disconnected;
- The total amount of energy required over this period.

The three quantities itemised above are easily derived from a charging choice. So the charging choice, as we defined it, reconcile the perspectives of driver and CSP.

The definition of charging choice we gave above can be further simplified. Consider the instant the vehicle is connected to the grid. Such instant can only be coincident with or delayed from to the arrival time to the charging facility. From the electric car driver's perspective, the start of the charging operation could be viewed as coincident with the arrival time, regardless of when the actual energy transfer may start. The simplification described makes it possible to represent in smart charging (whatever the strategy) and conventional charging through the same simple attributes:

- The amount of energy available in the battery after charging, hereafter target energy (E);
- The time it takes to obtain E since the arrival at the charging facility, hereafter effective charging time (ECT);
- The charging cost (CC).

An EV driver will evaluate alternative charging options based on E, ECT and CC. The utility that EV drivers associate with an option will vary depending on their idiosyncratic preferences and the context in which they make their charging choices. EV users may seek to charge their vehicle as fast as they wish depending, for example, on the flexibility of their departure time or their perceived risk of unanticipated vehicle use before the planned departure. They also may seek battery levels consistent with their planned travel distances and with buffers allowing for the uncertainty they associate with their travel plans, as well as the uncertainty they associate with driving range predictions.

This conceptual framework, inter alia, takes into account preferences of EV "charging level" standards (I, II, III), which describe the maximum charging speed a charging point can deliver. The higher the charging levels the shorter charging times. Therefore, "charging level" preferences are expressed by the contribution of ECT in determining the utility a driver can attain from a charging option. Understanding preferences for charging levels can enable planning charging infrastructure requirement based on the demand for the specific standard.

In summary, our conceptual framework for charging choice builds on the finding of the charging behaviour literature as follows. It captures the effect of range preferences in charging decisions, by means of the contribution of E to the utility drivers attained by charging their EV. Additionally, it accounts for the effects of travel patterns (e.g. travel distance) on charging decisions as observable contributions to the heterogeneity in preference for the three charging attributes. Finally, we account for unobservable heterogeneity in charging behaviour by specifying empirical models using random parameters that are distributed so to describe the variability of preferences for E and ECT across the drivers.

## 2.2. A visual representation

To clarify the concept of charging choice adopted in this paper, and its relationship to the users and the CSP perspective, consider Fig. 1.

Fig. 1a shows the concept of charging choice as proposed in this study. At a given charging opportunity, drivers choose their target state of charge (SOC) and effective charging time. The SOC is a representation of the battery level as a fraction of the total battery capacity. The charging choice space is constrained by the maximum charging rate, the SOC before charging ($SOC_0$) and the maximum battery capacity (SOC = 100%). The maximum charging rate in SOC per unit time is the slope of the left boundary line of the light grey areas in Fig. 1. A particular charging alternative is represented by a (target SOC, ECT) point in the feasible charging choice space. We should point out, that in Fig. 1, the maximum charging rates are shown as constant. In reality, however, these are a function of the SOC, typically slowing down for high SOC levels. In the picture, these are presented as constant purely for simplicity of exposition, but whether charging rates are a function of SOC does not affect our concept of charging choice; it simply changes slightly the shape of the choice space.

Fig. 1d depicts a stepwise charging profile that a CSP may impose to a vehicle. Such charging profile may be the result of the CSP operational management process that optimises the energy distribution to several EVs. Each EV could connected to the grid at a different time, $t_0$, and request different target states of charge and effective charging times. The vectors of $t_0$, target SOC and ECT would enter as constraints in CSP's operational management optimisation.

As the charging profiles would be chosen by the CSP, the drivers will not know in advance their vehicles state of charge at any moment. This uncertainty may induce the strongly risk averse to prefer choosing to charge at the maximum charging rate, i.e. choosing target SOC, ECT points that belong the left boundary line of light grey area of the graphs of Fig. 1. These risk averse choices correspond to inflexible load. Less risk averse drivers will make choices away from the boundaries of the light grey area. Choices away from the boundaries of the light grey area allows the CSP to flexibly determine the charging profile. In fact, the CSP might incentivise highly flexible choices with the devising a suitable tariff structure for the charging service.

## 2.3. A random utility model for charging choices

The charging choice space of Fig. 1 is depicted as continuous within its boundaries. However, in practice drivers would face discrete options, when setting their charging preferences via a smart charging device. This justifies modelling charging choices as discrete choices.

The standard approach for discrete choice analysis is based on the theoretical framework of random utility (RUT) (Ben-Akiva and Lerman, 1985; Train, 2009). According to RUT, decision makers are assumed to choose the alternative that maximises their own utility from a set of mutually exclusive alternatives. RUT accommodates the analyst's inability to describe perfectly the utility attained by the decision maker by specifying the utility $U_i$ of the alternative $i$, as the sum of a function $Vi$ ($X_i, \beta$) of the attributes of the alternative $X_i$ and an error term $\varepsilon_i$. The parameters $\beta$, in linear-in-parameter utility formulations, represent the marginal utilities with respect to the attributes of the alternative $i$ ($X_i$), and are also called taste parameters. The error term accounts for the unobserved utility (i.e. the analyst's ignorance) as well as for measurement and specification errors. Note that the utility for an alternative, in general, varies across individuals. Thus in theory each individual has his/her own utility function. However in practice, heterogeneity is captured by using individual characteristics as covariates and by opportunely breaking up the error term so that the idiosyncratic component can be meaningfully interpreted as random heterogeneity.[2]

In this work, we specify the utility attained by choosing charging alternative i as a function of the target energy of that alternative $E_i$, its effective changing time $ECT_i$ and its charging cost $CC_i$:

$$U_i^{Ch} = V_i^{Ch} + \varepsilon_i^{Ch} = V_i^{Ch}(f(E_i, ECT_i, CC_i), \beta) + \varepsilon_i^{Ch} \qquad (2.1)$$

A driver will chose alternative i if all the other alternatives in his/her choice set give a lower utility.

The formulation above as well as that of the theoretical models in Sections 2 and 3 omit representing the fact that utilities are individual-specific to avoid proliferation of subscripts. The empirical models, detailed in Section 4, will however capture individual heterogeneity.

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[2] We refer to Train (2009) for details on capturing taste heterogeneity in discrete choice models.
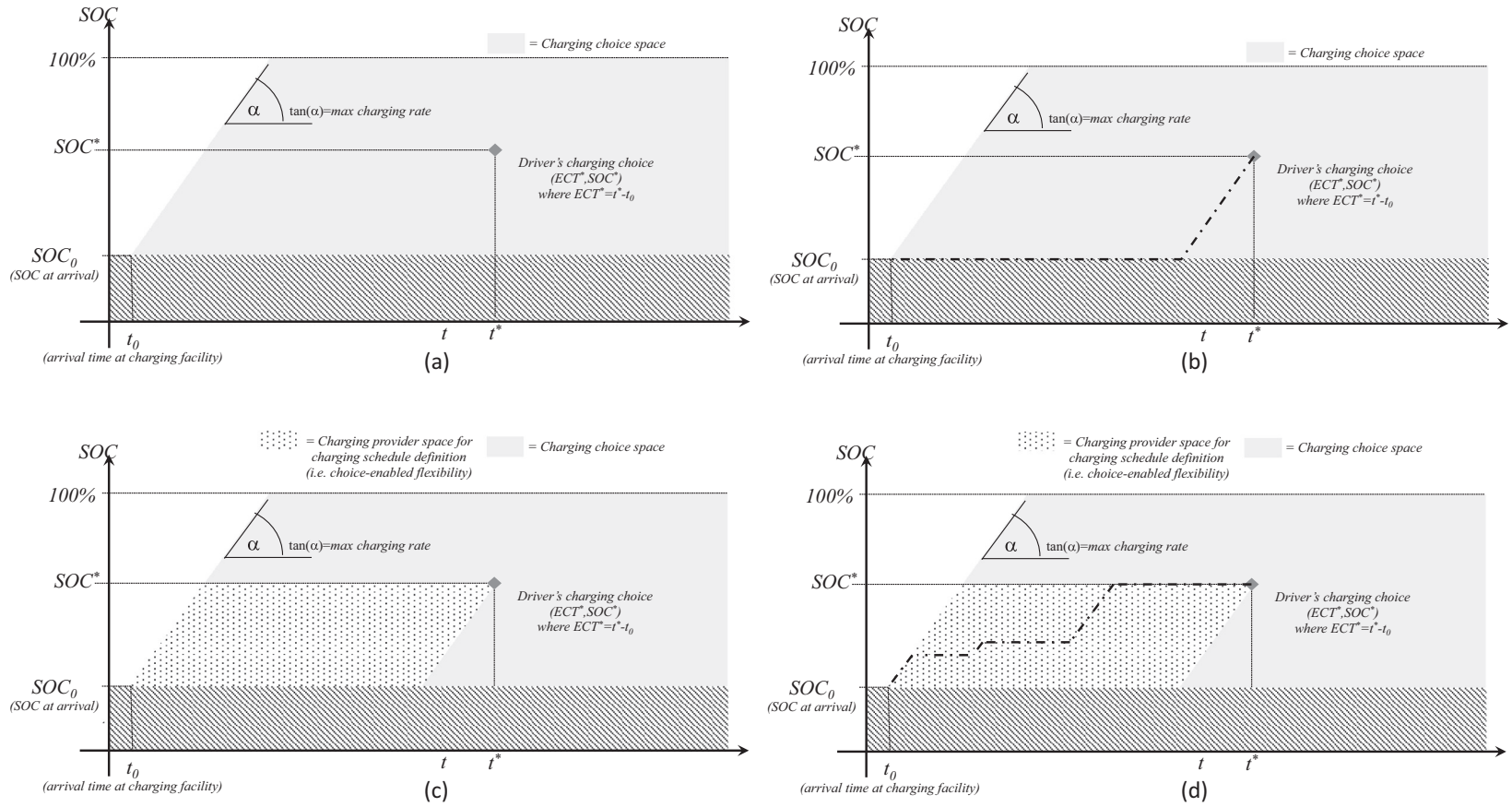
**Fig. 1.** Conceptual view of a charging choice. Graph (a) shows the dimensions the charging choice. Graph (b) shows a possible charging schedule underlying charging choice, where an EV driver delays the charging start time to take advantage of lower electricity prices. Graph (c) shows the space leeway available to a charging service provider underlying the charging choice. Graph (d) is an example of charging schedule resulting from accepting external control of the charging operation by a charging service provider.

## 3. Joint random utility model of charging and activity-travel timing choice

Daily activity and travel behaviour and charging behaviour present manifold interrelated choice dimensions. Charging choices, and corresponding values E and ECT, are intertwined with the dimensions of daily activity-travel choices. Amongst these interactions, the relationship between charging choices and timing choices of activities and travel is of particular interest when modelling the effect of smart charging strategies and the tariff structures of the charging services. Consider for example to following two scenarios.

A common scenario of residential electricity pricing is a two-period time of use pricing, in which electricity is cheaper at night. In such a case, EV drivers spending enough time at home during the night, would most likely charge overnight and not consider delaying their departure in the morning just to extend the duration of the charging operation, as this second option would not provide any benefits.

As alternative scenario we take one in which the electricity generation mix with significant penetration of wind power. In this second scenario, there may be days in which moderate wind is forecasted during the morning hours at times when usually drivers depart their homes. Using such forecasts, the CSP might offer very low charging prices for vehicles plugged-in early in the morning. In this case, some drivers might consider delaying their departure, if their travel plans are flexible. The charging choice and departure time choice thus become joint decision.

The modelling framework we develop here account for these types of interactions. In order to do so we embed the charging choice dimension into the random utility modelling framework for activity and travel timing decisions traditionally used for choice of time of travel under road pricing.

### 3.1. Activity-travel scheduling choice

Most of the studies analysing the choice of the time of travel are based on the idea of Vickrey (1969) that individuals have a preferred time of travel and that any shift from that preferred time that causes disutility. These shifts are called schedule delays. A version of Vickrey's theoretical model was estimated empirically as discrete choice model for trip timing choices using revealed preference data by Small (1982). In this paper, we adopt the extended version of the Vickery-Small model that takes into the trip chain nature of travel patterns (Polak and Jones, 1994; de Jong et al., 2003; Hess et al., 2007). The archetypal trip chain used in activity based analyses is called a tour. A tour is a trip chain that starts and ends at the same location. In this extended formulation, the observed component of the utility for a two-leg tour j is expressed as (Hess et al., 2007):

$$V_j = \beta_{SDL}SDL_j + \beta_{SDE}SDE_j + \beta_{DL}DL_j + \beta_{TT}TT_j + \beta_{TC}TC_j + \beta_{PD}PD_j + \beta_{PI}PI_j \qquad (3.3)$$

In the equation above $TT_j$ is the total travel time (i.e. the sum of the contributions of two legs of the tour), $TC_j$ is the total travel cost (i.e. the sum of the contributions of two legs of the tour). $SDL_j$, $SDE_j$ are schedule delays and $PI_j$, $PD_j$ are activity participation penalties, defined as:

$$
\begin{aligned}
SDL &= \max(t_d - t_d^*, 0) \\
SDE &= \max(t_d^* - t_d, 0) \\
PD &= \max(T^* - T, 0) \\
PI &= \max(T - T^*, 0)
\end{aligned}
\qquad (3.4)
$$

$t_d$ is a generic departure time and $T$ a generic activity duration. The starred quantities identify the respective preferred departure time and duration. $SDL_j$ ("schedule dealy late") and $SDE_j$ ("schedule delay early") are late and early shifts from the preferred departure time respectively. $PI_j$ and $PD_j$ are the increase and the decrease in duration w.r.t the preferred duration of the activity between the two trips of the tour. $DL_j$ is a dummy variable capturing the jump in disutility if the schedule delay late is different from zero. Activity participation penalties account for the disutility of expansion and contraction of activity participation along the tour that results from activity and travel timing decisions.[3]

### 3.2. Accounting for the utility of charging

We now extend the scheduling choice model described above to model EV use scheduling and charging (EVUSC) choices. To achieve this, we make the following broad assumptions:

- Individuals make their charging decisions once they arrive at a location where charging is available, having in mind their next travel requirements;
- They decide when to depart jointly with the charging decision as the duration of the charging operation may or may not affect their departure time;

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[3] Note that in a trip chain formulation such as that one described above, the schedule delay terms appears only for the first trip of the chain, because in the subsequent trips the effect of delays is confounded with activity participation penalties.

- Such joint decision affects 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: E, ECT, and CC.

The assumption to model jointly the choices related to a portion or an entire day's activities and travel schedule is common in activity based modelling. In the previous subsection we have mentioned the case of tours, but in general activity-based modelling views demand for activity and travel is "as a choice among all possible combinations of activity and travel in the course of a weekday" (Bowman and Ben-Akiva, 2001). Our approach is thus in line with activity based modelling literature.

The modelled charging choice is myopic, because a driver considers at each charging and scheduling decision only the current charging opportunity, disregarding other charging opportunities that may occur after the current. 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 (2013).

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.

Fig. 2 shows the activity-travel episodes that constitute the setting for each EVSUC choice. Each choice refers to a charging opportunity and the activity-travel episode that spans between the arrival time to the location with the current charging opportunity and the arrival time to the next charging opportunity. In the figure such an episode is illustrated between vertical dashed lines.

The utility of an EVSUC is the sum of two terms: one referring to the charging operation and one referring to the corresponding activity-travel episode. Let $U_{ij}$ be the EVUSC's utility, where $i$ indicates the charging alternative and j the activity-travel timing alternative at a given charging opportunity. $U_{ij}$ can be written as

$$U_{ij} = U_i^{Ch} + U_j^{AT} \tag{3.5}$$

where $U_i^{Ch}$ was defined in equation (2.1) and $U_j^{AT}$ is the utility of the activity travel episode with timing options $j$. If we assume a linear specification for $U_i^{Ch}$, expression (2.1) becomes:

$$U_i^{Ch} = \beta_E E_i + \beta_{ECT} ECT_i + \beta_{CC} CC_i + \varepsilon_i^{Ch} \tag{3.6}$$

We specify $U_j^{AT}$ using a schedule delay formulation for a trip chain. The activity travel episode $j$ is constituted of a chain of $N_a$ activities each followed by a trip. The chain starts at charging opportunity and concludes with a trip to a location with a charging opportunity. $U_j^{AT}$ is given by:

$$U_j^{AT} = \beta_{SDL} SDL_j + \beta_{SDE} SDE_j + \beta_{DL} DL_j + \beta_{TT} \sum_{k=1}^{k=N_a} TT_{k_j} + \beta_{TC} \sum_{k=1}^{k=N_a} TC_{k_j} + \sum_{k=2}^{k=N_a} (\beta_{PD} PD_{k_j} + \beta_{PI} PI_{k_j}) + \varepsilon_j^{AT} \tag{3.7}$$
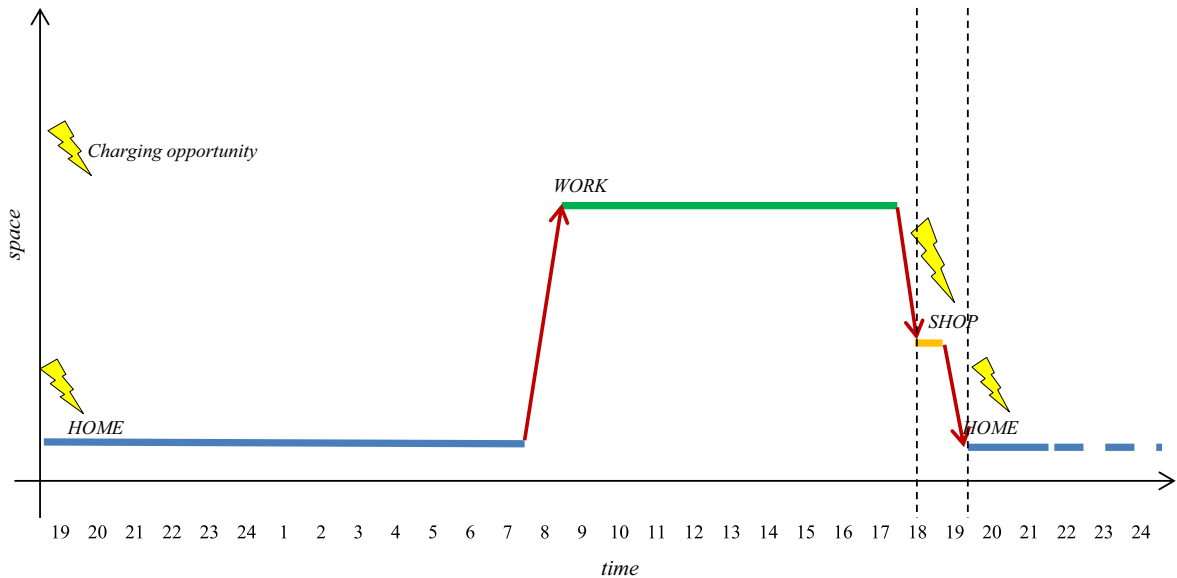


**Fig. 2.** Charging opportunities and activity-travel episodes. Each choice refers to a charging opportunity and the activity-travel episode before the next charging opportunity. One episode is comprised between two consecutive vertical dashed lines.

where $SDE_j$ and $SDL_j$ are outbound schedule delay early and late with respect to the preferred departure time for the first trip in the chain. $DL_i$ is a dummy variable capturing the jump in disutility if $SDL_j$ is different from zero. $PD_{k_j}$ and $PI_{k_j}$ are the activity participation penalties for activity $k$ undertaken within the activity-travel episode, after departure. In particular $PD_{k_j}$ is a decrease in participation time and $PI_{k_j}$ an increase. $TT_{k_j}$ and $TC_{k_j}$ are the travel times and the non-fuel travel costs, respectively. $\beta_X$, where the subscript $X$ is generic, are model parameters representing the marginal utilities.

Note that the choice set of EVUSC options available to EV drivers has an additional congruence constraint apart from those given by the battery storage capacity and the maximum charging power, which is:

$$t_0 + ECT_i \leqslant t^* + SDL_j - SDE_j \tag{3.8}$$

where $t_0 + ECT_i$ is the chosen end time of the charging operation. The meaning of the constraint above is that the choice of charging duration ($ECT$) is bounded by the departure time from the charging facility. In order to obtain separate estimates for $\beta_{ECT}$, $\beta_{SDL}$ and $\beta_{SDE}$, a choice situation in which the constraint is non-binding for some of the alternatives is required.

Schedule delay and activity participation penalties for each of the $N_a$ activities in the activity chain capture the conditional dependency of the EVUSC on the duration of the activity between the two charging events. However, a limitation of this model is the fact that it is myopic, i.e. it does not take into account future charging opportunities in EVUSC decisions, but only the current one. This means that it does not take into account the conditional dependency of the choices made in multiple interchanging intervals. Nevertheless, in urban areas where home (overnight) charging can usually provide for the range needed throughout a day this limitation is deemed negligible. There exist models that take into account activity participation choices over multiple days (Chow and Nurumbetova, 2015). These could potentially be used to model individuals' EV use and charging planning choices over longer time horizons considering multiple charging opportunities. Such a model extension is beyond the scope of the present work, which aims at the detailed modelling of tactical charging choices, at their occurrence, and their related trade-offs.

### 3.3. EVUSC utility a simple home-based two-leg tour

In order better to 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 (Fig. 3), instead of a general activity-travel episode.

In this case, assuming a linear specification for $V_i^{Ch}$, the utility for an EVUSC alternative can be written as:

$$
\begin{aligned}
U_{ij} &= V_i^{Ch} + V_j^{AT} + \varepsilon_{ij} \\
&= \beta_E E_i + \beta_{ECT} ECT_i + \beta_{CC} CC_i + \beta_{SDL} SDL_j + \beta_{DL} DL_j + \beta_{SDE} SDE_j + \beta_{PI} PI_j + \beta_{PD} PD_j + \beta_{TT}(TT_{1_j} + TT_{2_j}) + \beta_{TC}(TC_{1_j} + TC_{2_j}) + \varepsilon_{ij}
\end{aligned}
\tag{3.9}
$$

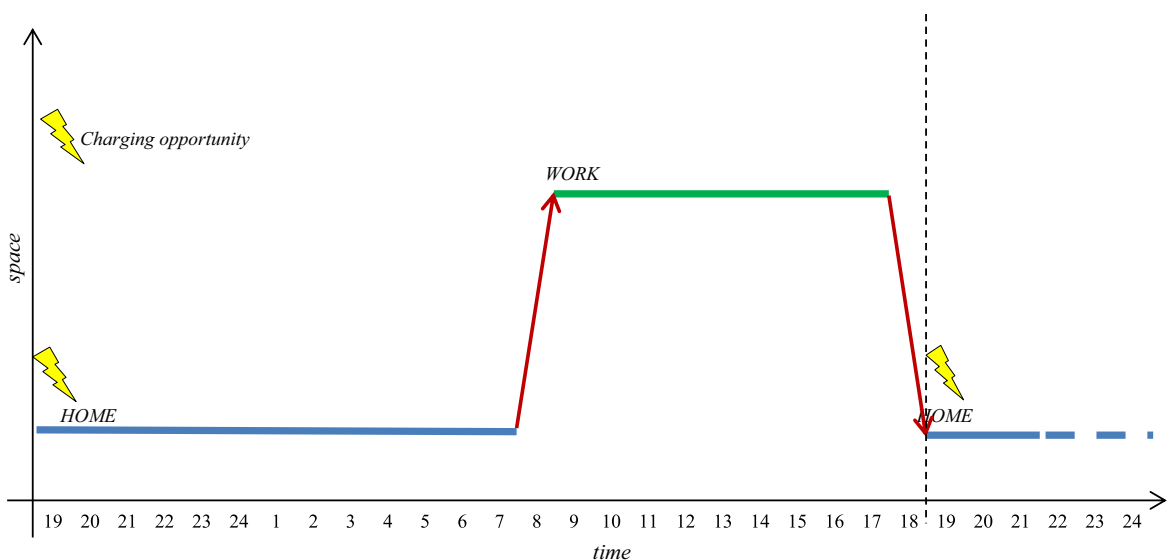where $\varepsilon_{ij} = \varepsilon_i + \varepsilon_j$.



**Fig. 3.** When only home charging is considered to be available, the unit of analysis becomes a home-based tour. This constitutes the setting used in the stated choice experiments for the empirical analyses described in the next section.

The meaning of the expression above is that EV drivers, when planning their EV use, adjust their departure times from home, and their activity participation at their destination, by taking account of travel time and travel cost changes, just as conventional car drivers do. They also, however, choose charging durations and target energy levels by responding to charging costs. The expression above allows for situations in which EV drivers may trade schedule delay late levels with target energy levels. For example, at a charging facility with a fixed charging power, they may opt for a longer charging time, to obtain a higher target energy level, at the cost of a delay (note that in this case the constraint (3.8) holds with the equality sign).

The weights (i.e. the values $\beta_X$) that charging and travel attributes have in EV charging and use scheduling choices need to be estimated empirically. The variability of such weights across individuals needs also to be estimated. The empirical estimates of $\beta_X$ determine how charging cost, target energy, effective changing time or schedule delays, etc. are traded one another in such choices. Estimating their heterogeneity across individuals enables capture the extent to which such trade-offs vary across individuals.

Indeed the home-based tour version of the model is easily amenable to empirical estimation making use of 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.

## 4. Empirical analyses: home charging choices

We adopt the modelling framework presented above in order to analyse home charging choices from stated (charging) choice experiments. In the experiments, hypothetical settings were designed such that the subjects (drivers) were required to charge their vehicle in order to undertake the next home based tour, without having the possibility to charge at the destination(-s).

### 4.1. The ECarSim data collection tool and its charging choice experiments

The charging choice data used for the empirical analysis presented in this paper were collected in 2012 as part of a PhD research project on charging behaviour (Daina, 2014). The choice experiments were part of a broader computer aided personal interview survey called ECarSim. ECarSim is an extension of the reflexive survey concept which was developed in order to collect data about unfamiliar hypothetical situations, while mitigating the potential negative effects of this unfamiliarity on the response reliability (Kurani et al., 1996). ECarSim is an internet-based interactive tool consisting of three parts:

(a) A questionnaire on socio-demographic characteristics of the respondents and a one car diary;
(b) A stated adaptation of the respondents' travel diary to an EV diary, including the specification of the charge timing, in a setting of conventional charging with constant charging power;
(c) A stated choice experiment section consisting of two types of tasks: a charging and tour scheduling choice.

ECarSim is specifically addressed to car drivers who in most cases have never operated an electric car. They are thus expected to have little or no familiarity with the charging operation and what this may entail for their travel patterns. In order to mitigate potential bias caused by lack of familiarity with EV we use the stated adaptation section of the survey. The stated adaptation makes respondents think about the potential effects of limited range recharging times and how charging operations can be accommodated in a typical day. Respondents are asked to set up the charging operation and possibly adapt their car diary in order to accommodate the use of an electric car with characteristics matching those of the Nissan Leaf. This section of the questionnaire thus serves as a "reflexive section" to engage respondents and smoothly introduce them to the hypothetical world for the charging choice exercises.

The stated choice experiments are the main data generation process of ECarSim in terms of eliciting charging behaviours in a hypothetical smart charging scenario. In this scenario, the smart charger requires as input data only the target battery level and the time this is to be achieved, "Time EV ready". Once these data are entered, the smart charger dashboard provides information about the cost of the charging operations. Respondents are told that "the price of electricity to charge your electric car will vary depending on how fast you want your electric car ready with a given battery level, and on the time of day you charge."

Respondents face two series of 12 choice situations. In the first series (discrete choice experiment 1, DCE1), after being reminded of the features of their first tour of the day, they are asked to choose between two alternative settings (which, henceforth are referred to as alternatives A and B) for the charging operation occurring during the vehicle dwell time at home before the tour. In this series, the ECT of an alternative never exceeds the original observed dwell time at home. The design variables are E, the ECT and CC. The battery level before charging and the start charging time are fixed across alternatives as well as across choice situations. While the former is also fixed across individuals, the latter is individual-specific. An example of choice situation in DCE1 is shown in Fig. A1 (Appendix A).

The choice attribute levels are the following:

- Four target battery levels (i.e. E levels). These are spread between the minimum energy to charge to make the tour feasible and the maximum energy that can be charged into the battery, given the battery state of charge before charging, the battery capacity (24 kW h) and the maximum charging power (7.2 kW).
- Four levels of charging operation duration (i.e. ECT levels). These are spread between a minimum given by the time to charge the minimum energy to make the tour feasible at the maximum charging power and the original vehicle dwell time at home.
- CC levels are obtained by three unit price levels multiplied by the amount of energy charged in the corresponding alternative.

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

Although the alternatives were generated only based on the three design variables described above, these were presented to the respondent in an extended form to ensure sufficient clarity in their description. It is worth mentioning here that the target battery level is also described in terms of the corresponding available driving range. This range is presented as an interval, to remind respondents that for a given battery level the range may vary, depending on their driving style, use of heating or air conditioning and road/traffic conditions.

In the second series of choice situations (discrete choice experiment 2, DCE2), the charging operation may exceed the original vehicle dwell time at home. Moreover, instead of a simple binary choice, respondents are offered options to partially absorb the schedule delay late by decreasing the time spent at the main destination of the home based tour. Up to four activity contraction options are offered for each of the two charging alternatives, depending on the original dwell time at the destination and the schedule delay level of the alternative. Finally, in the second choice experiment, respondents have the alternative to avoid charging and to use another mode, or to suppress the tour entirely. An example of choice situation in DCE2 is shown in Fig. A2 (Appendix A).

To keep the choice experiments simple, no other external disturbances on the activity-travel chain were considered, apart from, in certain choice alternatives, charging operation durations long enough to induce schedule delays late. In addition, for such alternatives, the variations in travel times resulting from the schedule delays were excluded from the experiments; i.e. drivers were presented alternatives in which travel times (or travel costs) would not vary across alternatives. In such conditions a (linear) specification of the utility for a EVUSC option is

$$U_{ij} = \alpha_{ij} + \beta_E E_i + \beta_{ECT} ECT_i + \beta_{CC} CC_i + + \beta_{SDL} SDL_j + \beta_{DL} DL_j + \beta_{PD} PD_j + \varepsilon_{ij} \tag{4.1}$$

In particular, for the first choice experiment, the basic form for the utility specification is

$$U_i = \alpha_i + \beta_E E_i + \beta_{ECT} ECT_i + \beta_{CC} CC_i + \varepsilon_i \tag{4.2}$$

where the index $j$ was dropped because the travel patterns are fixed in the first choice experiment. For the second choice experiment, the utility for an EVUSC option is specified as

$$U_{ij} = \alpha_{ij} + \beta_E E_i + \beta_{CC} CC_i + \beta_{SDL} SDL_j + \beta_{DL} DL_j + \beta_{PD} PD_j + \varepsilon_{ij} \tag{4.3}$$

Note that only activity participation penalties at the destination, corresponding to a decrease in activity duration ($PD_j$) are retained in the specification, because a reasonable response to a charging-induced schedule delay may be curtailing the activity at the destination.

Screen shots of the DCE1 and DCE2 as they appear in ECarSim are provided in Appendix A. Additionally a summary of the attributes presented in the two choice experiments is shown in Table 1. Further details on ECarSim and the design of the choice experiments can be found in Daina's PhD thesis (Daina, 2014).

## 4.2. Empirical model specification

The choice experiment data and the specifications described above are used with two error term assumptions:

  I. $\varepsilon_{ij}$ iid Extreme value type I distributed, leading to a logit model (McFadden, 1974); and
 II. Coefficients $\beta_E$, $\beta_{ECT}$ and $\beta_{SDL}$ independently normally distributed and $\varepsilon_{ij}$ iid Extreme Value type I distributed, leading to a random coefficient mixed logit model to capture unobserved taste heterogeneity for the EVSUC attributes (McFadden and Train, 2000).

In addition to capturing unobserved heterogeneity using mixed logit specifications, we attempt also to capture systematic variations in EVSUC preferences by interacting alternative attributes with

- Individual characteristics;
- Planned activity-travel characteristics exogenous to the setting of the choice experiments;
- Indicators of tour flexibility.

**Table 1**
Alternatives' attributes in choice experiments DC1 and DC2.

| Charging choice experiments | DC1 | DC2 |
|---|---|---|
| Attributes of choice alternatives | Target energy E | Target energy E |
| | Effective charging time ECT | Schedule delay late SDL |
| | Charging costs CC | Charging costs CC |
| | – | Activity participation decrease at destination (PD) |

**Table 2**
Descriptive statics of choices in DCE2.

| Alternative | | Availability | Availability % | Times chosen | Times chosen % | Times chosen when available % |
|---|---|---|---|---|---|---|
| Charging alternative A | PD level high[a] | 776 | 73% | 67 | 6% | 9% |
| Charging alternative A | PD level mid[a] | 740 | 70% | 25 | 2% | 3% |
| Charging alternative A | PD level low[a] | 712 | 67% | 23 | 2% | 3% |
| Charging alternative A | PD = 0[a] | 1056 | 100% | 289 | 27% | 27% |
| Charging alternative B | PD level high[a] | 790 | 75% | 74 | 7% | 9% |
| Charging alternative B | PD level mid[a] | 754 | 71% | 22 | 2% | 3% |
| Charging alternative B | PD level low[a] | 728 | 69% | 17 | 2% | 2% |
| Charging alternative B | PD = 0[a] | 1056 | 100% | 278 | 26% | 26% |
| Avoid charging and travelling | | 1056 | 100% | 34 | 3% | 3% |
| Avoid charging and use other mode | | 1056 | 100% | 227 | 21% | 21% |

[a] PD is the activity participation decrease at destination.
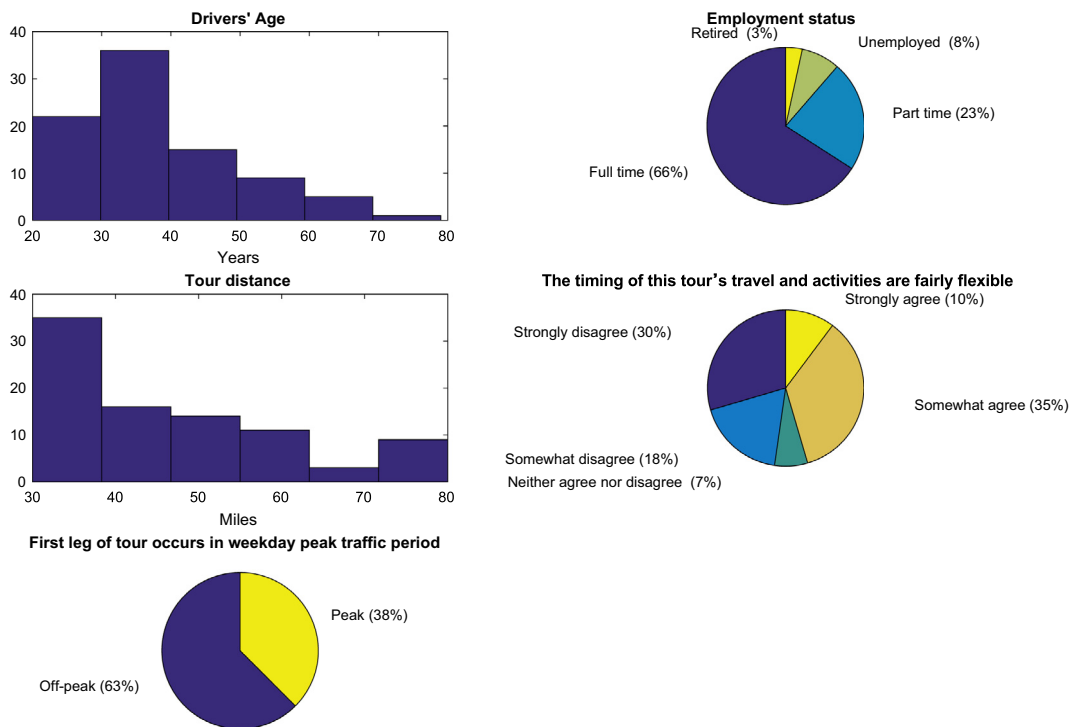


**Fig. 4.** Descriptive statistics of respondents' characteristics and tour characteristics.

While a variety of specifications for these interaction terms were tested, in the results shown in this paper we present specifications that attempt to balance parsimony, goodness of fit and interpretability.

We conducted a specification search estimating a large number of models with different specifications for the systematic portion utility, in order to achieve the final specifications presented in Section 4.4. These resulting specifications were chosen

to provide a good balance between goodness of fit and parameter interpretability as it is common practice in DCM estimation (Ortuzar and Willumsen, 2011).

In particular, in our specifications' search the interaction terms between alternative attributes and individual specific variables (i.e. individual characteristics and activity-travel characteristics) are chosen to reflect of a priori notions of possible effects. Amongst these effects, the planned travel driving distance is expected to affect the marginal; utility for E; demographic variables as it are expected to affect the cost parameter; flexibility of travel and other journey characteristics such as travel in peak time period are expected to affect the marginal disutility of schedule delays. More details on the interpretation of these interaction terms is reported in the results' section.

### 4.3. Dataset descriptive statistics

The number of car drivers in the dataset used for model estimation is 88. For each choice experiment, a respondent faces 12 choice situations, therefore the datasets consist of 1056 observations for DCE1 and 1056 for DCE2. As DCE1 is a binary choice between two generic charging choice alternatives (A and B), we observed only a slightly higher number of choices for alternative A (561) than for alternative B (495). For DCE2 alternatives, availability and choice statistics for the sample are reported in Table 2. We observed that a charging alternative is chosen for 75% of the choice situations. Unsurprisingly, when respondents find charging alternatives unattractive, they tend to state a preference for a shift in mode rather than for travel suppression.

The descriptive statistics of respondents' characteristics, and the tour characteristics used to specify interaction terms in the utility specification, are reported in Fig. 4. Amongst the car drivers in the sample over 47% are aged 35 or younger, and the majority (66%) are in full employment. About 55% of the tours respondents are expected to drive after charging have a distance that is between 30 and 40 miles inclusive, while for the remainder the tours are longer than this. The first leg of 38% of those tours is completely or in part driven in peak traffic hours. 48% of the tours are considered inflexible in timing.

It should be pointed out that selecting drivers who frequently (i.e. at least once weak) carry out a tour of a fairly long distance (between 30 and 80 miles) and designing the hypothetical charging choice situations for the choice experiment around those tours was a deliberate survey design decision, motivated by the necessity to make the choice situation particularly meaningful to the respondents given the considerable fraction of battery capacity required to drive such distances (Daina, 2014).

### 4.4. Estimation results

We present in this section models' estimation results. These were obtained using in part BIOGEME (Bierlaire, 2003) and in part using MATLAB codes written by the authors.

Specifications, parameter estimates, and relevant model statistics are reported in Table 3 (logit) and Table 4 (mixed logit) for DCE1; and Table 5 (logit) and Table 6 (mixed logit) for DCE2.

The logit estimates from DCE1 (Table 3) show a positive marginal utility of E, a marginal utility of ECT that changes sign across the sample and a negative cost coefficient. Considering the effect of systematic variations, at planned driving distances above 40 miles, we observe that a positive jump in the marginal utility of E occurs and a variation in sign from positive to negative of the marginal utility of ECT. The cost coefficient varies with age and employment status. This variation is such that the cost coefficient is larger in magnitude for younger people and smaller for individuals in full time employment. These systematic effects are all also significant in the mixed logit specification, bar the effect of the employment status on the cost coefficient.

A positive marginal utility of E is unsurprising. Similarly, the strong dependence on the driving distance of the marginal utility of E is unsurprising. When a journey is longer the consequences associated with remaining stranded are higher and thus the utility attached to higher available ranges is larger.

The sign variation in the marginal utility of ECT across the planned driving distance levels is an unexpected result and deserve further investigation. Notwithstanding, if we assumed that this unexpected result is "behavioural", it would mean that individuals planning to drive shorter distances prefer having the vehicle charged just in time for departure, whereas those planning longer travel have a preference for having the charging operation finished well ahead of departure time. We note that preferences for shorter ECT and for higher E when planning longer trips are consistent with risk aversion. Longer trips increase the exposure to uncertain events, which might cause delays and require range-consuming detours. Given this uncertainty, a vehicle charged earlier than the planned departure with higher range buffers seems a reasonable cautionary response.

Nevertheless, potential hypothetical biases or survey design effects could not be ruled out, as causes of the dependence on distance of marginal utility of ECT. Therefore, our interpretation of this dependence should be treated as speculative.

The mixed logit specification (Table 4) increases the overall goodness of fit of the model. The significance and size of the standard deviations under the assumption of independently normally distributed $\beta_E$ and $\beta_{ECT}$ in the mixed logit specification show that a large portion of the heterogeneity in a taste for E and ECT remains unobserved, beyond the systematic variation captured in model specification.

**Table 3**
Logit model estimates based on charging choices in DCE1.

| Variable | Coefficient | Std err | t-test | p-value | Robust Std err | Robust t-test | p-value |
|---|---|---|---|---|---|---|---|
| Charging alternative A | 0 (fixed) | NA | NA | NA | NA | NA | NA |
| Charging alternative B | −0.00273 | 0.0774 | −0.04 | 0.97 | 0.077 | −0.04 | 0.97 |
| CC [GBP] | −0.459 | 0.0712 | −6.45 | 0 | 0.0694 | −6.62 | 0 |
| CC * (Age ≤ 35) [GBP] | −0.292 | 0.0616 | −4.73 | 0 | 0.0622 | −4.69 | 0 |
| CC * (Employed full time) [GBP] | 0.141 | 0.0647 | 2.18 | 0.03 | 0.065 | 2.17 | 0.03 |
| E [kW h] | 0.0521 | 0.0167 | 3.12 | 0 | 0.0159 | 3.27 | 0 |
| E * (planned driving distance > 40 mi) [kW h] | 0.355 | 0.0303 | 11.75 | 0 | 0.0317 | 11.19 | 0 |
| ECT [10 h] | 0.488 | 0.0807 | 6.06 | 0 | 0.0776 | 6.29 | 0 |
| ECT * (planned driving distance > 40 mi) [10 h] | −1.04 | 0.129 | −8.04 | 0 | 0.133 | −7.83 | 0 |
| **Number of observations** | 1056 | | | | | | |
| **Null log-likelihood** | −731.963 | | | | | | |
| **Final log-likelihood** | −521.8 | | | | | | |
| **Rho** | 0.287 | | | | | | |
| **Adjusted rho** | 0.276 | | | | | | |

**Table 4**
Random coefficient mixed logit estimates based on charging choices in DCE1.

| Variable | Coefficient | Std err | t-test | p-value | Robust Std err | Robust t-test | p-value |
|---|---|---|---|---|---|---|---|
| Charging alternative A | 0 (fixed) | NA | NA | NA | NA | NA | NA |
| Charging alternative B | −0.0205 | 0.0988 | −0.21 | 0.84 | 0.078 | −0.26 | 0.79 |
| CC [GBP] | −0.721 | 0.123 | −5.87 | 0 | 0.14 | −5.15 | 0 |
| CC * (Age ≤ 35) [GBP] | −0.305 | 0.114 | −2.67 | 0.01 | 0.145 | −2.11 | 0.03 |
| CC * (Employed full time) [GBP] | 0.0964 | 0.123 | 0.79 | 0.43 | 0.142 | 0.68 | 0.5 |
| E [kW h] | 0.0834 | 0.0506 | 1.65 | 0.1 | 0.0409 | 2.04 | 0.04 |
| E * (planned driving distance > 40 mi) [kW h] | 0.597 | 0.0881 | 6.78 | 0 | 0.0995 | 6 | 0 |
| ECT [10 h] | 1.13 | 0.222 | 5.1 | 0 | 0.179 | 6.31 | 0 |
| ECT * (planned driving distance > 40 mi) [10 h] | −1.99 | 0.334 | −5.96 | 0 | 0.357 | −5.58 | 0 |
| **St. dev. of ind. normal parameters** | | | | | | | |
| $\sigma_E$ | 0.309 | 0.0437 | 7.06 | 0 | 0.0472 | 6.54 | 0 |
| $\sigma_{ECT}$ | 0.977 | 0.176 | 5.57 | 0 | 0.204 | 4.8 | 0 |
| **Number of draws** | 10,000 | | | | | | |
| **Number of individuals** | 88 | | | | | | |
| **Number of observations** | 1056 | | | | | | |
| **Null log-likelihood** | −731.963 | | | | | | |
| **Final log-likelihood** | −442.722 | | | | | | |
| **Rho** | 0.395 | | | | | | |
| **Adjusted rho** | 0.381 | | | | | | |

We show the probability density functions of the marginal utilities of E and ECT for the estimation sample in Fig. 5. The empirical distribution of marginal utility of E shows that 78% of the mass of the distribution is above zero, but a still considerable 22% is below zero. Clearly the assumption of a normally distributed parameter necessarily implies that this will have a mass both above and below zero. Observing that nearly the 80% of the sample value E positively is reassuring, as it is reasonable that higher ranges are generally preferred to lower ones. However, a 22% negative mass in the distribution of the marginal utility of E deserve further investigation. This negative mass could be the result of a binary choice in DCE1 that forces a choice even between alternatives that may both be unattractive to the respondents. We note that in DCE2, where respondents can avoid unattractive charging alternatives, the distribution of marginal utility of E shows that 90% of the sample value E positively. The empirical distribution of the marginal utility of ECT highlights a considerable variation in sign across the sample, already highlighted in the logit model.

For the models estimated using data from DCE2 (Tables 5 and 6), we observe that the marginal utility for E is intuitively positive. In the mixed logit model, 90% of the mass of the empirical distribution of the marginal utility of E is positive (Fig. 6). Both SDL and CC have negative coefficients. In the mixed logit model 90% of the mass of the empirical distribution of the marginal utility of SDL is negative (Fig. 6). The disutility for SDL is intuitive as it signals disutility for late departures w.r. t. a preferred departure time.

The effect of the activity participation penalty PD is insignificant for the charging alternatives. However, if the activity is totally cancelled (i.e. for the alternative "avoid charging and travelling"), the number of hours lost affects the utility for this alternative (the longer the lost activity at the destination, the higher the disutility).

In the models for DCE2 we also estimates constants that capture baseline preferences for (1) EV charging and use, (2) avoid charging and travelling, and (3) avoid charging and shift mode. We observe a stronger preference for the first option

**Table 5**
Multinomial Logit model estimates based on charging choices in DCE2.

| Variable | Coefficient | Std err | t-test | p-value | Robust Std err | Robust t-test | p-value |
|---|---|---|---|---|---|---|---|
| Avoid charging and travelling | 0 (fixed) | NA | NA | NA | NA | NA | NA |
| Avoid charging and travelling * PD [h] | −0.189 | 0.0557 | −3.39 | 0 | 0.0251 | −7.53 | 0 |
| Avoid charging and use other mode | 0.938 | 0.294 | 3.2 | 0 | 0.225 | 4.17 | 0 |
| Charge and use EV | 2.64 | 0.404 | 6.53 | 0 | 0.38 | 6.95 | 0 |
| Charge and use EV * (planned driving distance > 40 mi) | −3.39 | 0.607 | −5.58 | 0 | 0.695 | −4.88 | 0 |
| Charging alternative A | 0 | fixed | | | | | |
| Charging alternative B | 0.0388 | 0.0902 | 0.43 | 0.67 | 0.093 | 0.42 | 0.68 |
| PD [h] | −0.11 | 0.133 | −0.83 | 0.41 | 0.16 | −0.69 | 0.49 |
| CC [GBP] | −0.153 | 0.0428 | −3.57 | 0 | 0.0435 | −3.52 | 0 |
| CC * (Age ≤ 35) [GBP] | −0.0652 | 0.0339 | −1.93 | 0.05 | 0.0329 | −1.98 | 0.05 |
| CC * (Employed full time) [GBP] | −0.075 | 0.0359 | −2.09 | 0.04 | 0.0345 | −2.17 | 0.03 |
| E [kW h] | 0.0537 | 0.0158 | 3.39 | 0 | 0.0179 | 3 | 0 |
| E * (planned driving distance > 40 mi) [kW h] | 0.164 | 0.0297 | 5.52 | 0 | 0.034 | 4.82 | 0 |
| DL | −1.96 | 0.213 | −9.23 | 0 | 0.222 | −8.85 | 0 |
| SDL [h] | −0.416 | 0.17 | −2.45 | 0.01 | 0.183 | −2.28 | 0.02 |
| SDL * (planned driving distance > 40 mi) [h] | −0.115 | 0.155 | −0.74 | 0.46 | 0.17 | −0.68 | 0.5 |
| SDL * (Peak time travel) [h] | −1.14 | 0.199 | −5.74 | 0 | 0.254 | −4.49 | 0 |
| SDL * (Inflexible activity travel timing) [h] | −1.62 | 0.197 | −8.24 | 0 | 0.269 | −6.03 | 0 |
| **Number of observations** | 1056 | | | | | | |
| **Null log-likelihood** | −2207.224 | | | | | | |
| **Final log-likelihood** | −1481.387 | | | | | | |
| **Rho-square** | 0.329 | | | | | | |
| **Adjusted rho-square** | 0.322 | | | | | | |

**Table 6**
Random coefficient mixed logit model estimates based on charging choices in DCE2.

| Variable | Coefficient | Std err | t-test | p-value | Robust Std err | Robust t-test | p-value |
|---|---|---|---|---|---|---|---|
| Avoid charging and travelling | 0 (fixed) | NA | NA | NA | NA | NA | NA |
| Avoid charging and travelling * PD [h] | −0.23 | 0.0591 | −3.88 | 0 | 0.0726 | −3.16 | 0 |
| Avoid charging and use other mode | 0.675 | 0.317 | 2.13 | 0.03 | 0.598 | 1.13 | 0.26 |
| Charge and use EV | 3.67 | 0.532 | 6.91 | 0 | 0.953 | 3.85 | 0 |
| Charge and use EV * (planned driving distance > 40 mi) | −6.05 | 0.865 | −7 | 0 | 1.84 | −3.28 | 0 |
| Charging alternative A | 0 (fixed) | NA | NA | NA | NA | NA | NA |
| Charging alternative B | 0.0769 | 0.114 | 0.68 | 0.5 | 0.126 | 0.61 | 0.54 |
| PD [h] | −0.0956 | 0.135 | −0.71 | 0.48 | 0.384 | −0.25 | 0.8 |
| CC [GBP] | −0.316 | 0.0698 | −4.53 | 0 | 0.0985 | −3.21 | 0 |
| CC * (Age ≤ 35) [GBP] | −0.143 | 0.0639 | −2.24 | 0.03 | 0.0818 | −1.75 | 0.08 |
| CC * (Employed full time) [GBP] | −0.052 | 0.0667 | −0.78 | 0.44 | 0.09 | −0.58 | 0.56 |
| E [kW h] | 0.0918 | 0.0252 | 3.64 | 0 | 0.0316 | 2.9 | 0 |
| E * (planned driving distance > 40 mi) [kW h] | 0.276 | 0.0457 | 6.05 | 0 | 0.0835 | 3.31 | 0 |
| DL | 0.432 | 0.374 | 1.15 | 0.25 | 0.449 | 0.96 | 0.34 |
| SDL [h] | −3.97 | 0.998 | −3.98 | 0 | 0.992 | −4 | 0 |
| SDL * (planned driving distance > 40 mi) [h] | 0.817 | 1.08 | 0.76 | 0.45 | 0.992 | 0.82 | 0.41 |
| SDL * (Peak time travel) [h] | −3.33 | 1.02 | −3.27 | 0 | 0.936 | −3.55 | 0 |
| SDL * (Inflexible activity travel timing) [h] | −5.93 | 1.14 | −5.19 | 0 | 0.998 | −5.94 | 0 |
| **St. dev. of ind. normal parameters** | | | | | | | |
| $\sigma_E$ | 0.0872 | 0.0134 | 6.48 | 0 | 0.0155 | 5.62 | 0 |
| $\sigma_{SDL}$ | 4.93 | 0.57 | 8.65 | 0 | 0.7 | 7.04 | 0 |
| **Number of draws** | 10,000 | | | | | | |
| **Number of individuals** | 88 | | | | | | |
| **Number of observations** | 1056 | | | | | | |
| **Null log-likelihood** | −2207.224 | | | | | | |
| **Final log-likelihood** | −1252.898 | | | | | | |
| **Rho** | 0.432 | | | | | | |
| **Adjusted rho** | 0.424 | | | | | | |

if the travel distances are low (below 40 miles), all else equal. For longer travel distances, the first option is preferred the least, all else equal.

As in DCE1, in DCE2 the variation in planned travel distance captures a systematic variation in preference for E. The taste for SDL is not affected by planned travel distance. Instead, a systematic variation in taste for SDL is observed as a
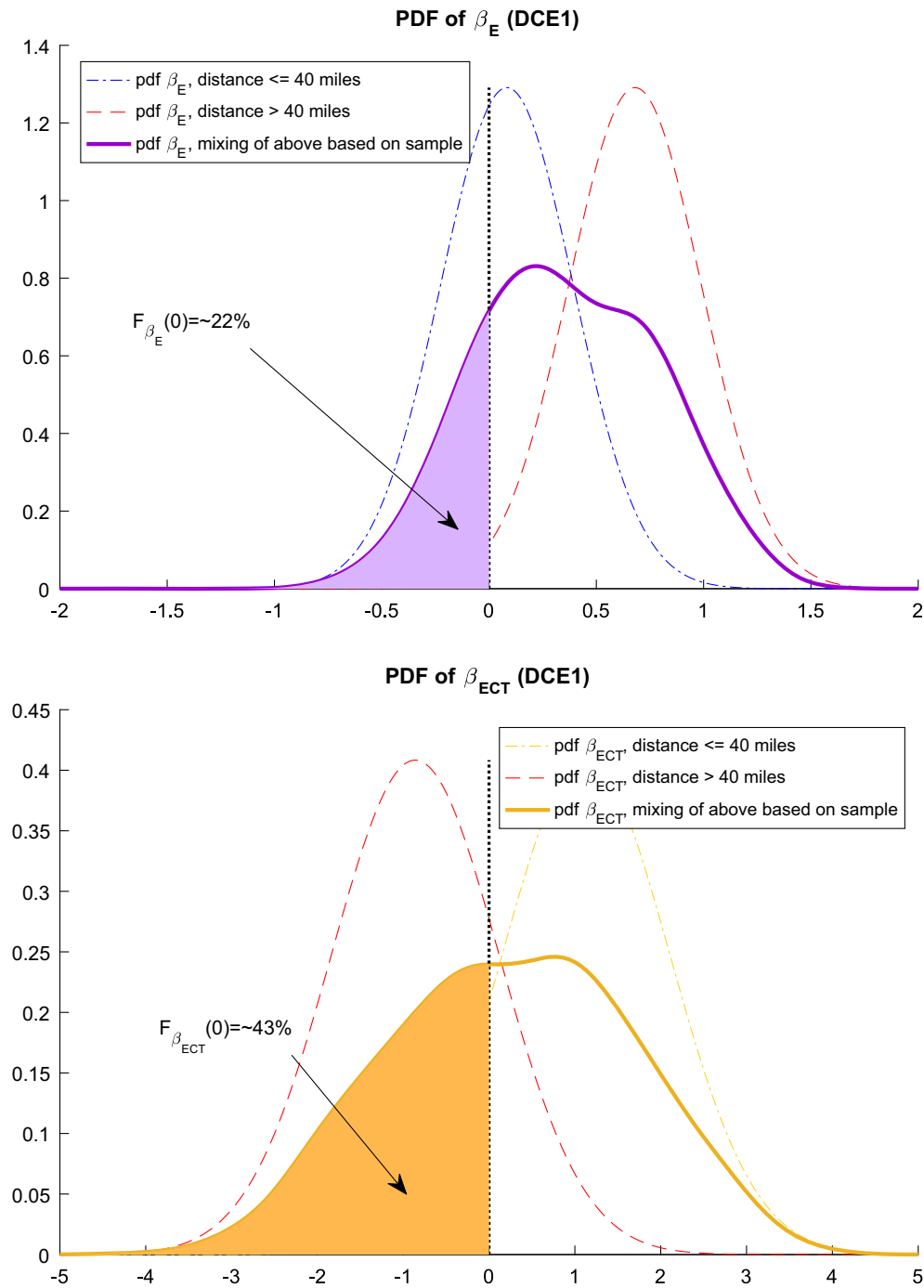
**PDF of $\beta_E$ (DCE1)**



Legend (top chart):
- pdf $\beta_E$, distance <= 40 miles
- pdf $\beta_E$, distance > 40 miles
- pdf $\beta_E$, mixing of above based on sample

$F_{\beta_E}(0) = \sim 22\%$

**PDF of $\beta_{ECT}$ (DCE1)**

Legend (bottom chart):
- pdf $\beta_{ECT}$, distance <= 40 miles
- pdf $\beta_{ECT}$, distance > 40 miles
- pdf $\beta_{ECT}$, mixing of above based on sample

$F_{\beta_{ECT}}(0) = \sim 43\%$

**Fig. 5.** Probability density functions of random coefficients in the mixed logit model based on DCE1 data.

function of whether one plans travelling in peak times and of whether one considers inflexible the time of their travel. In particular, both peak time travel and travel inflexibility increase the disutility for delays. The systematic heterogeneity in the cost coefficient is captured by age, but not by employment status, consistently with the results from the mixed logit results from DCE1. In terms of goodness of fit, unsurprisingly, also for DCE2, the mixed logit has a better performance than the logit specification.
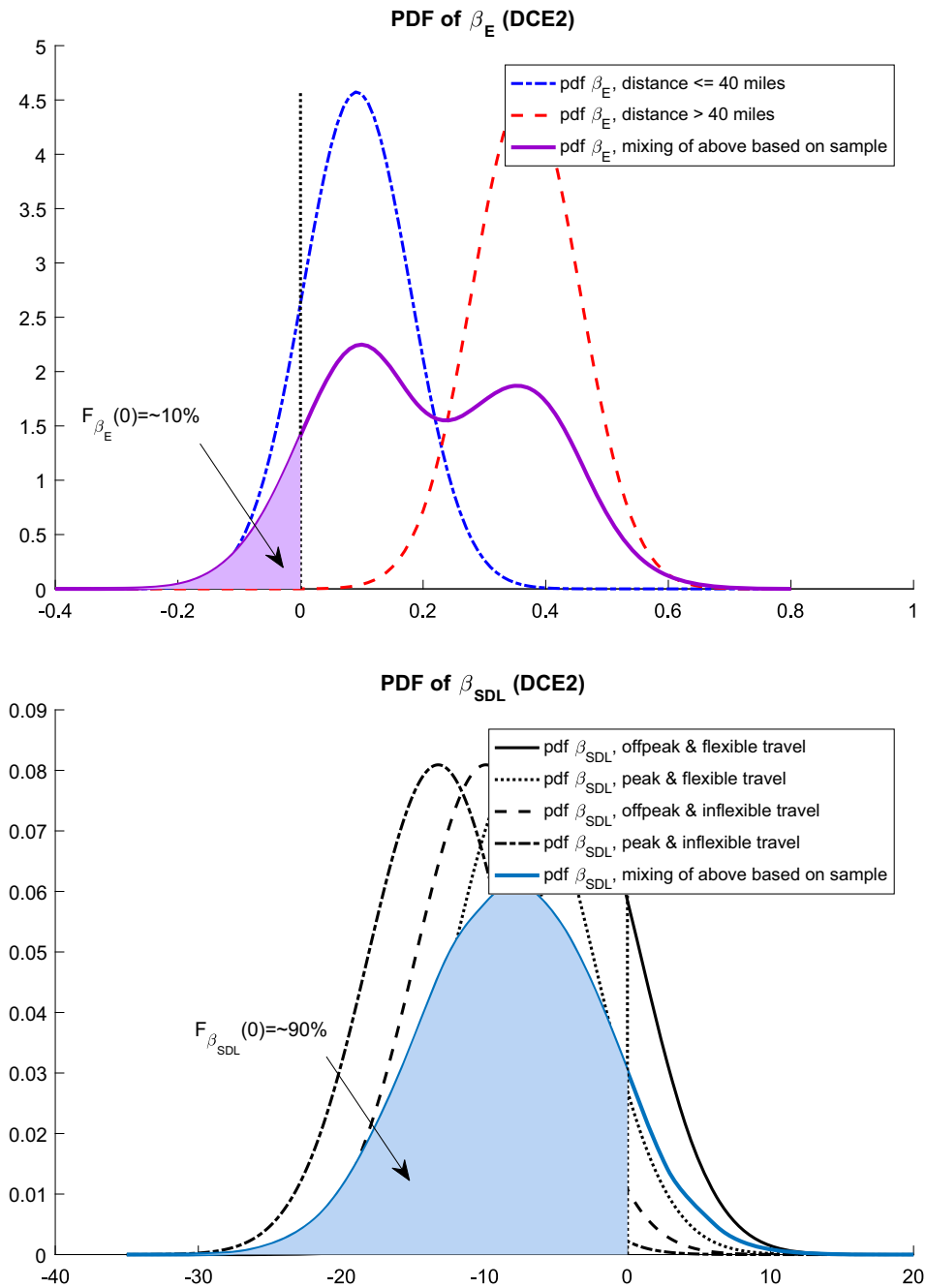
**Fig. 6.** Probability density functions of random coefficients in the mixed logit model based on DCE2 data.

## 4.5. Implications

Overall, the results of this first empirical implementation of the conceptual and modelling framework introduced in this paper highlighted a potentially large preference heterogeneity that may affect charging choices in smart grid contexts.

An important implication of the potential heterogeneity in charging behaviour uncovered here is that analyses of the impact of electric vehicle deployment typically obtained by making use of charging behaviour scenarios deserve caution. Individual preferences and specific travel needs may induce EV drivers to respond differently to smart charging offerings,

and therefore charging behaviour scenarios designed to represent the effect of smart charging strategies in impact analyses may greatly overestimate of such strategies.

Our results also suggest interesting implications for the operations of charging service providers. If the valuation of ECT is indeed as heterogeneous as our results suggest, and such heterogeneity is not a spurious effect of our survey instrument, charging service providers could make use of such heterogeneity. Assuming that they will have enough observations to classify drivers along the ECT preference dimension, they could "extract flexibility" from those more inclined to longer ECTs without incentives. On the other hand, they could charge a premium for "inflexibility" to those preferring quick charging operations. Such a premium may induce some drivers to switch to more flexible charging options, depending on their cost sensitivity. More generally, consumer heterogeneity in charging preferences could by exploited in revenue management strategies for charging services.

The main limitation of the analytical results presented above is that they are not readily generalised to the entire population of UK drivers due to the small sample available in our dataset. Notwithstanding this, we believe that the useful insights on charging behaviour obtained in this paper provide a basis for further exploration of charging behaviour in smart grid contexts. Our insights can guide the design of additional choice experiments, that ideally could be administered to a larger a more representative sample of the drivers population over specific geographical areas of interest.

## 5. Conclusions

The integration of the road transport and power systems requires the exploitation of EV load flexibility by implementing smart charging services. The effectiveness of smart charging services need appraisal through modelling. The state of the practice of integrated transport and energy analyses for the appraisal of smart charging services rely on simplistic representation of charging behaviour that are not policy sensitive or theoretical models that lack strong empirical foundations.

Our work bridges the gap between the representations charging behaviour used in integrated transport and energy system analyses, and the literature of charging behaviour studies. We bridge this gap by developing a random utility model for joint EV drivers' activity-travel scheduling choices and charging choices. Our model easily integrates in activity-based demand modelling systems for the analyses of integrated transport and energy systems. However, unlike previous charging behaviour models used in integrated transport and energy system analyses, our model empirically captures the behavioural nuances of tactical charging choices in smart grid context.

We estimate empirical versions of the model using data from two discrete choice experiments. Our empirical results provide insights into the value placed by individuals on the main attributes of the charging choice. These attributes target energy (E), effective charging time (ECT) and charging cost (CC).

We found that E tended to have a positive marginal utility for a large majority of drivers in our sample: 80–90%, depending on which choice experiment is considered. This result is intuitive and was in accordance with our expectations, because a positive marginal utility for E means that drivers prefer higher range levels.

The result for the marginal utility of ECT is more mixed and therefore more interesting. When charging levels do not induce schedule delays, the marginal utility of ECT is positive for about 60% of the drivers in our sample and negative for the rest. Therefore, when charging does not induce delays the majority of our sample of drivers prefer keeping the vehicle under charge as long as they are at home. Only 40% of the sample prefer charging as fast as possible. The split in preference sign for ECT across the sample is minimum when the effective charging duration induces late departures. 90% of drivers accrue less utility from alternatives with higher schedule delays, all else being equal.

The significant heterogeneity in the valuation of E and ECT levels has important implications. First, heterogeneity in charging behaviour suggests that the use of fixed charging behaviour scenarios in the analysis of the impact of EV charging management strategies may misrepresent the load from EV charging. In addition, heterogeneity implies that charging service providers could incentivise more flexible charging choices with targeted actions for "inflexible drivers". Indeed, charging service providers could exploit the segmentation in charging behaviour for their revenue management strategies.

The insights provided by our empirical work should be further validated in studies with larger samples and revealed preference data in addition to choice experiment data. However, the characterisation of charging behaviour preferences enabled by our analytical framework opens the way for further studies on the behavioural response to smart charging and vehicle-to-grid services. We recommend that further research in this direction is pursued, as revealed preference data becomes available with increased market penetration of EVs.

## Acknowledgments

**Appendix A**



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

**Fig. A1.** Example of choice situation in DCE1.

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



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

**Fig. A2.** Example of choice situation in DCE2.

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