Electric vehicles: a fair way to go

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Abstract

The transition to Electric Vehicles (EVs) has been acknowledged by many governments as a key means to reduce emissions from the transport sector. The current work has focused on the technical challenges and benefits of EVs, yet the adoption of new technologies can often expose new inequalities. In the case of EVs, purchase costs are high and a new inequity arises; those with the ability to connect their car at home can access its storage capability and lower charging tariffs. There is therefore an urgent need to understand how policies will impact on different socioeconomic groups and the resulting challenges and opportunities for electricity system operators. This work seeks to answer three key questions:

1. What policies will best drive a socially equitable EV transition?
2. What are the technical impacts and opportunities presented by EV adoption from a socioeconomic perspective?
3. Can environmentally and financially sustainable public transport be integrated to support a socially equitable EV transition?

These questions are explored through two novel multi-scale models. An EV adoption and use simulation combines consumer behaviour modelling with travel data generating long-term EV adoption forecasts and 30 minute resolution charging patterns across eight different socioeconomic groups. And an electrified bus fleet techno-economic model integrates wind and solar generation, hydrogen production, energy storage and EV charging to explore environmental and financial sustainability alongside reducing costs for EV owners without home charging.

Bans on the sale of Internal Combustion Engine (ICE) vehicles are shown to be the only effective means to deliver a timely transition. Making it more equitable can be achieved by tailoring other policies so as not to disproportionately benefit generally wealthier early adopters whilst bringing forward the availability of lower cost used vehicles. Rural residents are shown to have greater impacts on network demands than city dwellers and lower income socioeconomic groups tend to impose the lowest impacts. In-car smart-charging algorithms can avoid, or defer, the need for network upgrades, whilst more sophisticated technologies can help support greater renewables integration at lower cost. Improving access to slow on-street charging can both facilitate better management of charging demands and, by linking street charging to consumers' home accounts, could help reduce tariff inequities. Finally, near-self sufficient electrified public transport systems are viable in some circumstances and could halve the cost of EV charging for those without access to facilities at home.

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Chapter 1

Introduction

1.1 Electric vehicles: what are they good for?

The deployment of EVs has the potential to reduce carbon emissions and also to improve local air quality (through reduced particulate and NOx emissions amongst others [60]). The extent to which EVs, and in particular, Battery electric vehicles (BEVs), reduce carbon emissions depends on the carbon intensity of electricity used for charging and there are some situations in which EVs, prior to adequate grid decarbonisation, may result in a net increase in carbon emissions [18]. However, the vast majority of situations, including that of the UK, result in very rapid payback of embodied carbon and as electricity networks decarbonise, so the benefits of EVs increase. Since solar and wind energy has close to zero marginal cost of production, smart grid systems that avoid curtailment of renewables by providing energy for transport use would seem desirable. Low-cost charging of EVs (during high wind/solar periods) can be delivered with relatively simple uni-directional controlled charging equipment; such control systems can also help to reduce the potential increase in local network peak demand and thus minimise reinforcement costs [174]. However, the full value of unused storage capacity in EVs can only be realised by Vehicle-to-Grid (V2G) technology. V2G enables controlled bi-directional power flows and can enable EVs to participate in the provision of a range of grid services such as frequency response [131, 196], reserve and peaking capacity [111], local voltage control [186] and arbitrage [125], effectively shifting renewable generation to times of higher demand. A simple analysis of the technical potential from V2G is set out in Box 1.1.

Box 1.1: the technical potential of V2G in the UK

To understand the potential of V2G to provide generation shifting services, a simple estimate can be determined using the following assumptions:

- The UK has around 30 million registered cars and light vans [224],
- Each vehicle travels, on average, 22 *miles* (35 *km*) per day [224],
- EV ranges greater than 250 *km* are desirable for wide scale uptake [74], thus an average vehicle range of 300 *km* would seem reasonable. This corresponds to a battery size of circa 75 *kWh* at 25 kWh 100 km^{-1} [106] for motorway driving (when longest range is required),
- V2G discharge never allows the battery to fall below 25 *kWh* (c120km range at extra-urban efficiency [106]), allowing an average of 50 *kWh* for V2G services.
- UK wind averages circa 30% load factor (across onshore and offshore facilities) and current installed capacity is 16.2 *GW*, giving an average of 4860 *MW* generation [59]; and
- a notional 50% participate in V2G at any one time.

The available stored energy (assuming fully charged at start) of the connected EVs is:

$50\ kWh \times 50\% \times 30,000,000\ vehicles = 750\ GWh$

This is equivalent to more than 6 days of average wind output at the current installed capacity, with each vehicle delivering just 0.324kW when connected (a discharge C-Rate of 0.004).

1.2 What are the down sides?

The deployment of electric vehicles presents a number of potential concerns including:

1. The additional demands placed on electricity networks from charging demands may require infrastructure investment and/or charge management.

2. A widening social equity gap since those with access to home charging can potentially operate their EVs at lower costs than those without.

3. Lower operating costs in general may result in an increase in private car use and lower the attractiveness of public transport, increasing congestion and particulate pollution from road and tyre wear.

4. The production of EVs requires the extraction of a wide variety of minerals to produce battery materials such as lithium, cobalt, manganese and copper; this extraction results in environmental degradation.

These considerations are not disconnected. Electricity network costs are driven by peak demands, yet a significant component of these costs are recovered from householders through a fixed daily charge regardless of household peak demand, or timing of that demand. This means that the cost of household EV charging has the potential to be distributed inequitably across consumers, with later adopters and those using public charging (where grid connection costs are paid by the installer) cross-subsidising those with home chargers. The extraction of materials for batteries required to balance the electricity system more generally can be minimised by maximising the utilisation of EV batteries through the the use of controlled charging and V2G services. Similarly, by encouraging the use of public transport where it is most effective, typically in urban areas, traffic congestion and residual pollution from road and tyre wear can be minimised. Combining effective public transport with EV use to provide an integrated service which also delivers public charging provision could assist in both reducing residual pollution and lowering the potential inequity in car charging costs.

1.3 What is needed to better understand the issues and opportunities?

Section 1.1 identifies some key literature concerning EV technical opportunities, with many more explored in Chapter 2. There is a similarly extensive body of literature exploring consumer attitudes to EVs and adoption, although rarely is this incorporated into the technical analysis. The literature exploring social equity issues is far less extensive, though there has been some more recent work in this area. Bauer, Hsu and Lutsey [21] specifically ask the question 'When might lower income drivers benefit from electric vehicles?' in their 2021 working paper for the International Council on Clean Transportation, but even here, the focus is on capital cost reduction of EVs. Whilst charging behaviours are incorporated, with an acknowledgement that lower income groups incur higher costs, their analysis, based on US rates and city/rural disparities suggests much lower charging cost differences that appear likely in the UK market and do not consider other possible benefits for home-chargers, such as smart charging tariffs, energy storage and V2G. In their 2018 review paper Sovacool et al. [202] identify weaknesses in the existing research in respect of the social dimensions, and human interaction with, V2G systems. They find that, of 197 V2G papers reviewed, 42% deal with renewables integration, 24% grid stability and ancillary services, 18% battery charging and degradation and 15% distribution level services; only 3% consider social acceptance, consumer norms and the informing of consumers. They further identify a number of under-examined areas:

- environmental performance,
- financial and business models,
- user behaviour,
- natural resource use,
- visions and narratives,
- social justice concerns,
- gender norms; and
- urban resilience.

A gap in the research exists in integrating social and behavioural aspects of EV adoption and use patterns to provide greater fidelity in the technical consequences and opportunities, and to explore how to better deliver a socially equitable transition.

Whilst EVs are widely regarded as the likely successors to fossil-fuelled cars, there is an acknowledgement from policy makers [68] that the issues set out at the start of this section cannot be addressed by a simple car replacement strategy. Greater emphasis needs to be placed on modal shift to public transport to reduce congestion, non-exhaust pollution and the wider environmental impacts of EV manufacture. Thus there is also a need to consider how EVs might integrate with zero-carbon public transport.

1.4 Research scope

The aim of this work is to explore the interfaces between human behaviours, social equity and technical outcomes in EV adoption and use, and to examine how the necessary shift to greater use of public transport can be developed in a sustainable fashion whilst also addressing EV charging inequalities. Since the objective of transitioning to EVs is to reduce carbon emissions, this subject is also explored in the context of the policies proposed.

Whilst much of the work presented here could be adapted for use in other countries, the scope is limited to the UK and validated against UK data. More specifically, the behavioral adoption model is based on data sourced from the National Travel Survey [223], which examines travel patterns in England only. No model can incorporate every aspect of human behaviour. This work focuses on a specific technique to emulate how consumers make purchase decisions and applies this to the purchase of cars, including EVs. The simulation does not apply behavioural modelling to charging strategies, but instead examines various scenarios. Predicting long term trends in anything is fraught with risk and, in the case of EVs, there are additional challenges presented by a disruptive technology that may also result in significant changes to future use patterns. This may occur either as a result of lower cost travel, which may be offset by as yet unknown policy interventions, or through the emergence of new travel modes such as Mobility as a Service (MaaS). This thesis does not consider such changes, but instead focuses on known historic vehicle usage to forecast potential future impacts of EV adoption and equitability. Whilst hybrid vehicles are included in the simulation, since these cannot deliver the government's 2050 net-zero target, they are not analysed in detail and as such the generic term EV refers predominantly to BEVs throughout this thesis.

The public transport component of this work introduces a model that can be applied in many situations involving buses. The specific case study presented here is based on a transport hub between Sheffield and Chesterfield, which has been proposed by a private developer in association with Derbyshire County Council. The outcomes in regard to self-sufficiency are specific to this site and the bus routes modelled, although a number of more widely applicable observations are made.

The specific questions to which answers are sought through this modelling fall into three broad categories:

1. What policies will best drive a socially equitable EV transition?
2. What are the technical impacts and opportunities presented by EV adoption

from a socioeconomic perspective?

3. Can environmentally and financially sustainable public transport be integrated to support a socially equitable EV transition?

Each of these questions are addressed through a number of more detailed questions set out at the beginning of each results chapter, as introduced in Section 1.6

1.5 Methodology overview

The research undertaken in this work employs agent-based modelling. Agent-based models (ABMs) provides a means by which the behaviour of individual elements, or agents, in this case cars and their owners, can be modelled with a set of rules that also govern the interaction between agents. Agent action is typically represented by a mixture of stochastic and deterministic behaviour. When the model is run, the interactions between agents generally result in an emergent behaviour pattern; for example, the growth curve in the uptake of EVs or the power demand profile resulting from their charging.

The results presented in this thesis are derived from two distinct ABMs:

- the 'Behaviour-based Electric Vehicle adoption and grid Integration' (BEVI) model; and
- the 'Renewables and Electric Vehicle Public Transport Integration' (REVIT) model

BEVI focuses on exploring how human behaviour and policy impact upon EV adoption and grid charging demands with the ability to generate data for various socioeconomic groups, income levels and geographic locations. It is able to simulate a range of charging scenarios from simple 'plug and charge' when available to a full V2G algorithm focused on balancing national renewable energy generation. The model is fully described in Chapter 3.

REVIT is a techno-economic model of electric and hydrogen buses operating from a single hub with on-site (or private wire, giving 'behind the meter' impact) wind and/or solar generation together with battery storage and hydrogen production and storage. The model accepts bus routes and schedules buses and charging events to meet the requirements of those routes. The hub facility also incorporates private car charging facilities. The REVIT model is fully described in Chapter 5.

1.6 Thesis structure

In this thesis, Chapter 2 presents a summary of the existing literature focusing on adoption modelling, grid impacts, policy and sustainable public road transport. Issues of social equity in the EV transition are also examined.

Chapter 3 provides a detailed description of the BEVI model with validation covered in Chapter 4. The REVIT model methodology and validation are set out in Chapters 5 and 6 respectively. The latter chapter also sets out details of the Derbyshire-based case study.

Three results chapters explore the the key questions identified in Section 1.4, each opening with a set of sub-questions related to the topic. Chapter 7 focuses on exploring policy impacts on EV adoption and social equity, Chapter 8 explores the technical outcomes of a posited suite of polices and the impacts on different socioeconomic groups including an exploration of V2G potential. Chapter 9 examines the financial and environmental performance of a renewable energy powered public transport hub and how it might alleviate charging cost disparities for those without access to home charging.

Finally, Chapter 10 identifies the achievements and short-comings of the simulations, sets out a summary of the conclusions against the research questions posed and sets out some areas for future work.

Chapter 2

Literature Review

This review is divided into the following sections:

1. What's missing? The need for social equity.
2. Behaviour and EV adoption modelling strategies.
3. EV adoption modelling using ABMs.
4. Validation of ABMs.
5. Policy analysis and policy modelling using ABMs.
6. EV grid services analysis and modelling using ABMs.
7. Transitioning away from personal transport.

The review starts by examining what is missing from the current research and then explores different ways in which these neglected areas could be modelled. This analysis is concluded by an assessment of the best approach to tackle the research questions posed and followed by further analysis of ABMs as the preferred technique. Finally, the last three sections explore the literature related to the research questions with a focus on those using ABMs for analysis.

2.1 What's missing? The need for social equity

There have, as the following sections will reveal, been numerous studies exploring the technical and economic potential of EVs and various surveys analysing EV adoption drivers and barriers, but social equity issues have been largely absent from the literature. These issues are however important; firstly behaviours and access to resources (not just capital but also knowledge and charging provision)

Figure 2.1: Why social equity matters in the transition to electric vehicles

are likely to have a significant impact on EV adoption and the availability of those EVs to provide useful network services. Secondly, the availability of home connections and consequent access to low-cost charging and/or benefits from V2G services have the potential to widen the gap between rich and poor, with those able to afford property with off-street parking able, for the first time, to fill their cars at much lower cost than those without such facilities (Figure 2.1).

Sovacool et al. [202] identified the lack of non-technical research in this area particularly in regard to V2G. They specifically noted that they found no references at all to 'social justice' or 'energy justice' within their searches. This is at odds with their noting that transport infrastructure and technology developments often benefit the more wealthy, whilst traffic congestion and resulting pollution more often afflicts lower income settings. Borenstein and Davis [27] identified that 90% of all EV tax credits had been received by the the top income quintile in the US; it seems likely that, with the high up-front cost of EVs, top-earners in other countries will also have received the lions share of benefits designed to increase adoption. This may, however, deliver societal value since these groups will be enablers of the technology, allowing volume to build and costs to come down whilst also, after a delay, providing access to used vehicles for the less wealthy. This later point is of significant relevance to cars, where a far greater proportion are purchased used than for other technologies. Higher earners also tend to drive more miles (See Table 2.1) so one can argue that delivering EVs to higher income groups is also a

Table 2.1: Average weekly mileage of drivers from the UK National Travel Survey [223], showing correlation between higher income and greater miles

Income Band (See Figure 3.12)	Average Weekly Mileage (miles)
1 (low)	102
2 (medium)	158
3 (high)	176

more cost effective way to reduce emissions.

Wells [235] explores issues around regional and intra-regional inequalities arising from policies to drive adoption of EV and the likelihood of mobility exclusion for some groups in society. Wells also notes that the presence of vehicle manufacturing in a country or region may affect the choice of focus for local policy making, perhaps reducing the emphasis on public transport in favour of personal mobility and that policies, at that time, favoured the affluent, inferring the potential for more considered policy approaches.

One of the only studies to explore social equity issues around home charging is that of Davis [49]; this is limited to an analysis of the US National Travel Survey (2017) in relation to home ownership, income and EV adoption. This showed a ’homeowner-renter’ gap for EV adoption where homeowners were three times more likely to own an EV than renters; this gap was shown to be significant even when controlling for income. This is considered to be the result of a number of factors, the two major considerations being that rental properties are less likely to have off-street parking to enable home charging and the effect of the "landlord-tenant" problem. This occurs because tenants do not wish to invest money to install a home charger in a property they don’t own, whilst landlords see little benefit in providing a charger since the next tenant may not drive an EV.

Fleming [88] set out a number of issues and policy recommendations regarding electric, automated and shared mobility services. The study highlights disparities between ethnicities in EV ownership, despite overwhelming support for climate action policies amongst the same group. Issues noted are the high initial purchase cost of EVs and lack of charging provision within those communities. In respect of policies, Fleming identifies the need to incentivise public transport and encourage walking and cycling to reduce congestion as well as emissions, but also the requirement to provide charging infrastructure within underserved communities. Interestingly, an income-cap on the availability of EV grants is also proposed, and has been implemented in California. The UK Government's recent removal of the grant for high cost EVs [10], could be seen as a proxy for this, although with the purchase cost of EVs, and BEVs in particular, still substantially higher than ICE vehicles, it is not clear that this policy will have any immediate impact on lower income groups. Fleming also proposes removing 'minimum parking' requirements within city planning rules and rather imposing 'maximum parking' limits so as to reduce parking availability and encourage the use of public transport.

Whilst issues of home charging availability are raised in some of the literature here, the options that might resolve that are largely unexplored. Various technologies do exist for installing street chargers and private companies have started installing these in the UK, e.g. Charg.gy [42]. However, charging costs are relatively high; for the example quoted, they range from 19.5p kWh^{-1} to 33p kWh^{-1} with no off-peak benefits; home off-peak charging is available from just 4.5p kWh^{-1} [72, 167]. Thus whilst solutions for those without home chargers are available, they have the potential to exacerbate inequality still further.

There is thus a need to understand adoption across social groups, the most equitable transition policies and means to enable lower cost charging for those unable to access home-based tariffs.

2.2 Behaviour and EV adoption modelling strategies

Understanding EV adoption rates is important from a number of perspectives. If EVs are to have a role in balancing electricity system demands, then their deployment, and the uptake of associated charging and V2G contracts, must progress in parallel with increasing renewables penetration. If EV adoption is slow, then more alternative sources of reserve power will be needed. These sources may be higher carbon (e.g. gas or diesel plant) or comprise static storage systems; either of these solutions will result in a collection of sunk-cost assets that may have marginal operating costs lower than V2G services and will therefore compete with V2G offers. Thus to avoid investment in static battery capacity and alternative reserve power sources, the rate of uptake of EVs must be understood relative to the need for such power reserves. The rate of uptake will also impact on local network demands, which may result in constraints requiring further network investment if suitable charging controls are not implemented; an understanding of where these constraints may occur and how they can be tackled is thus important for network operators. Finally, it is important to understand where and when the social equity issues raised in Section 2.1 may begin to have detrimental impacts, and how policies might be modified over time to ameliorate them.

Adoption rates for EVs have been modelled by a number of authors and can be divided into three model types; diffusion, consumer choice and agent based. Each of these types are discussed below.

2.2.1 Diffusion models

Diffusion models for the adoption of consumer durables, including cars, have been successfully deployed for many years. The underlying approach was first discussed by Rogers in 1962 [189]. In this work, Rogers identified the main components in the diffusion of new ideas as:

1. *Innovation* - an idea, practice or object perceived as new
2. *Communication Channels* - the means by which information about the innovation are transmitted between potential adopters. Rogers identified that most communication occurs between similar, or homophilous, individuals, but for innovation to diffuse it is often necessary to bridge heterophilous groups.
3. *Time* - plays a key role in the diffusion of innovation since potential adopters must first acquire knowledge then be persuaded before reaching a decision; in the case of EVs this time component is exacerbated by the long life time of cars.
4. *Social System* - this relates to the structures in place within the society in which the innovation is to be adopted and may be influenced by, for example, 'opinion leaders'.

Rogers introduced the adopter categorisations as illustrated in Figure 2.2, where the boundaries between adopter categories are multiples of standard deviations from the mean. Bass [20] was the first to apply mathematical rigour to the adoption and diffusion process described by Rogers, and the basic S-curve is now commonly referred to as Bass diffusion. Bass described the Rogers process as: *"The probability that an initial purchase will be made at time t given that no purchase has yet been made is a linear function of the number of previous buyers."*, and set this out as described in Equation 2.1.

$$P(t) = p + \frac{q}{m} Y(t) \tag{2.1}$$

where:

$P(t)$ probability of purchasing vehicle at time t

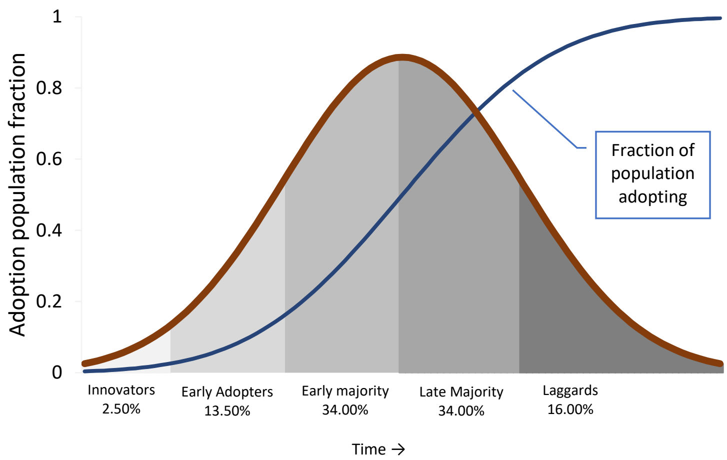


Figure 2.2: Adopter categorisation and innovation of diffusion after Rogers [189]

p	a constant representing the coefficient of innovation in the market
q	a constant representing the coefficient of imitation in the market
m	the number of initial purchases of the product
$Y(t)$	Number of previous buyers

Whilst the Bass diffusion model has been shown to effectively fit product sales growth, Chandrasekaran and Tellis [41] note that it has a number of limitations including:

- the model requires growth data from sales covering the two main inflexion points for forecasts to be made yet such data is not available at the time forecasting is most important;
- the model parameters are unstable and change as new sales data becomes available;
- there is no allowance for the effects of marketing or other external influences; i.e. it is not possible to model the impact of, for example, an advertising programme or, in regard to EV uptake, government incentives;
- the product definition is fixed, which is problematic for EVs as the technology is likely to evolve over the timeframe of interest; and

- identifying the start and end of sales is challenging due to product replacements.

Numerous modifications to the basic Bass model have been suggested to overcome these limitations; these modifications have been reviewed, inter alia, by Mahajan, Muller & Bass [146] and more recently by Meade and Islam [148]. None of the modifications proposed or implemented appear to have addressed all the issues concurrently. Adding additional complexity also renders the models less transparent and more open to instability in, and interaction between, model parameters.

Meade & Islam [148] use the adoption of residential telephones in the UK to show how drastically adoption can vary from the smooth curves predicted by Bass, and many modified Bass, processes. They further note the importance of both period-by-period demand (for the manufacturers of telephones) and overall penetration (for network peak demands). In relation to EV adoption, these can be translated to vehicle manufacturer period-by-period production requirements and the demands placed on charging infrastructure and the grid.

It is recognised that diffusion models do not reflect the adoption rates of eco-innovations so effectively as for time-saving or leisure enhancing products [101, 123]. Furthermore, new business models delivering 'eco-mobility' and changes to historical social practice, such as autonomous 'vehicle-on-demand' services may change the way in which society uses cars [162] and therefore the availability of EVs for V2G services. The rate of uptake is also likely to be heavily influenced by government policy and the regulatory environment. Many states have already put in place incentives for the purchase of EVs and a number have put forward proposals to ban the sale of pure fossil-fuelled cars [61, 161]. However, there is a challenge for governments in striking the right balance between demands for ever more mobility and environmental concerns [162] and doubts that political interventions will promote the most efficient solutions. Thus whilst a basic diffusion model may well replicate the overall adoption curve of EVs, it is not a practical method to simulate the effects of policies and technology innovations or to achieve the desired degree of granularity in analysing societal uptake and impacts on local networks.

2.2.2 Consumer choice models

Consumer preferences for Alternative Fuelled Vehicles (including hydrogen, synthetic fuels and electric variants) (AFV), have been examined extensively using stated preference surveys and conjoint analysis techniques [74, 98, 173, 195]. These studies highlight the attributes that are considered important by potential purchasers; price, range, speed of charging, cost of ownership etc. and Glerum et al. [98] further includes a more detailed examination of attitudes and perceptions. For example, their survey indicates that about half of buyers consider vehicle design to be a primary element in the purchasing decision; only about one third of respondents considered car purchase to be primarily about practical transport considerations. This in itself is a challenge for the introduction of entirely new power trains since it is not practical to introduce these across all segments (e.g. mini, lower medium, executive sports, etc.) of vehicle at the same time. This means that potential purchasers are very likely to reject an EV for reasons other than simply because it is electric.

The models discussed here employ multinomial logistic regression to predict possible choice outcomes; future forecasts are essentially based on utility decisions made by consumers and do not take into account either the ability of those consumers to make accurate cost-benefit judgements or the effect of word-of-mouth interactions between consumers. This latter point is generally considered a key determinant in the diffusion of new technologies [41]. Very often the models significantly constrain the number of choice options; whilst this is beneficial in ensuring transparency and a manageable set of choices for participants, it does reduce the fidelity of the model in regard to consumer decision making. Louviere and Woodworth [143] note that consumer choice models provide little information about how a consumer's choice might vary if presented with alternative choice sets and thus tend to reflect the market state at the time of the survey that informs it. In a fast evolving market, likely to include the development of EVs, it is difficult for such models to incorporate changes in technology and societal attitude over time.

Despite these shortcomings in consumer models, they provide valuable insight into consumer decision making processes. For example, Axsen et al. [13] have shown that whilst innovators have a preference for pure BEV vehicles, early adopters tend to prefer plug-in hybrid vehicles (PHEV), which may be due to a combination of familiarity and the lack of range anxiety with such vehicles. However, in a rapidly evolving market with improving vehicle range and charging infrastructure, the rigidity of this preference is questionable. They have indeed also shed light on the range requirements of consumers; for smaller pure battery EVs, Eggers [74] notes that ranges in the order of 250km appear acceptable, with a significant drop in popularity where the range drops to 150km, despite the average daily travel requirement being less than 50km. Further increasing range did not appear to increase acceptability in this car segment. However, for larger vehicles, range increases up to 350km tested by Eggers also showed increasing acceptability. Eggers does not include the availability of charging infrastructure within the model, though does make reference to its importance. Greene [103] reviewed a number of studies exploring the availability of fuels for AFVs and concluded that it is an important factor in vehicle selection, but that there is significant variability in how it is valued by consumers; in some cases, the purchase cost reduction of an AFV required to expedite its purchase being equal to the value of the vehicle itself. Whilst these studies were not focussed on BEVs, they provide a clear indication that availability of EV charging infrastructure will play a critical role in EV uptake. Home refueling, as is possible for many EV owners, opens a further complication in the analysis since many users could fulfil the vast majority of their travel needs solely from this source.

2.2.3 Agent based models

ABMs are a class of simulation that employs bottom-up modelling with individual actors, or agents, programmed with rules that are adaptable to each. These may include communications with other agents, who act upon the information received in some pre-determined manner. Through these rules and interactions, emergent behaviour across agents will normally arise. Agents may take many different forms within an EV related ABM; they may be consumers, vehicles, batteries, charging stations, manufacturers or other market actors. Individual agent rules and communications applied over time may lead to, for example, a shift in fuel type used or in most popular vehicle segment. ABMs have the advantage that bottom-up peer interactions can be readily integrated whilst also incorporating top-down policy and technology development drivers. However, ABMs have also been criticised for their lack of transparency [50, 142]. It can be challenging to understand the aggregate output from ABMs since the final result is the product of emergent behaviour from complex and often opaque interactions between multiple agents (consumers in this case).

Thiele et al. [209] note that parameterisation of ABMs is challenging, for example, there may be a lack of observational data or uncertainty in available data. For this reason Theile et al. note that many parameter values are chosen heuristically such that the key model outputs reflect real-world outcomes. Ideally, a knowledge of the sensitivity of the model to various parameters is required to understand relative importance and robustness.

Windrum et al. [237] sought to explore methods for empirical validation of ABMs. They identify that the goal of the modeller is to provide a sufficiently good approximation of real-world outcomes from a suitably simplified set of rules within the ABM. However, Windrum et al. also observe that models can either take a ’realism’ or ’intrumentalism’ approach. In the former, the modeller is generally attempting to replicate real-world actions and interactions. In the latter, the agents need not be true representations of real-world entities; the modeller’s objective is merely to produce a model that accurately forecasts real-world outcomes. Whilst an instrumentalist approach is useful in minimising inputs and thus potentially providing a more transparent model, such a strategy may also render the model less effective at dealing with changes in technology and policy that evolve (indeed may be evolved by the model itself) over time.

2.2.4 Conclusions on modelling strategy

Rennings [184] introduced the concept of eco-innovation, being measures that *"develop new ideas, behaviour, products and processes, apply or introduce them and which contribute to a reduction of environmental burdens or to ecologically specified sustainability targets"*. Rennings noted that analysis techniques were poorly developed at the time and put forward a set of ’determinants of eco-innovation". Figure 2.3 expands on Renning’s basic set of determinants to consider a range of factors specific to EVs. In general, diffusion models are largely limited to ’Market Pull’ elements whilst Consumer Choice Models are able to consider the impact of technology push and regulatory push on consumer behaviour and thus market pull. ABM models are the most flexible in that they can more readily enable market pull feedback to influence technology direction and the regulatory environment.

Al-Alawi and Bradley [3] reviewed market modelling studies for AFVs in their 2012 paper. The analysis considers the three main types of model discussed above; namely agent-based , consumer choice and diffusion rate.

On diffusion models, Al-Alawi and Bradley [3] note that they are relatively easy to implement, but that, since the time of peak sales is not known, parameterising the model cannot be effectively done and they are also not valid for modelling situations where competing products exist.

Consumer choice models, according to [3], are most useful where there is a substantial base of historical consumer preference data and they consider them to be more transparent than ABMs. The disadvantage is that those rich datasets do not exist for AFVs and purchasing decisions are complex and subject to many influencing factors that may not have been revealed in survey data. In general, consumer choice models determine purchase decisions based on the utility value of the specified vehicle to the group of consumers being modelled. Social interactions between individuals are not normally considered, although Struben and Sterman [207] have combined diffusion models with consumer choice models in

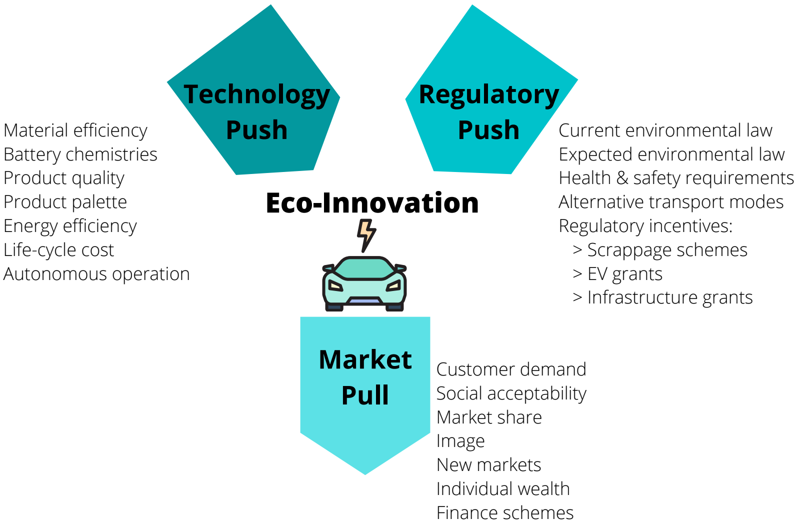


Figure 2.3: Determinants of eco-innovation in relation to growth of EV sales (after [184])

an attempt to overcome this limitation.

ABMs are noted as being useful in combining both "data-driven and hypothetical consumer behaviour" and allowing greater consideration of real world complexity and developments over time. The disadvantage is mainly seen as being in their complexity and difficulty in validation, although this can be overcome when there is sufficient market data for early adoption comparisons [121].

The objective of this research is to integrate aspects of human behaviour into an electric vehicle environment to draw out previous unexplored factors in EV adoption and use and how these will impact on adoption rates, electricity networks and social equity. It is thus important to select a modelling technique best able to integrate this human behaviour component; of the three main options discussed here, the ABM stands out as the most suitable.

2.3 EV adoption modelling using ABMs

This section reviews relevant ABMs that have been developed with EV adoption in mind. One challenge here is that, due to the very low numbers of BEVs in the market until recently, many of these models focus on hybrid cars. These cars do not share the same challenges, notably range anxiety, and thus do not require such a shift in mindset. Cao et al. [35] explored the concept of familiarity bias, or fear of the unknown, in regard to investments in stocks and shares and propose that emotions of fear and suspicion can explain various anomolies in economic and financial decisions. Given that the purchase of a new car presents a significant financial transaction, it seems likely that familiarity, or Status Quo, bias may play a more significant role in the purchase of BEVs compared to Hybrid Electric Vehicles (HEVs) or Plug-in Hybrid Electric Vehicles (PHVs).

One of the few studies to directly consider BEVs is that of Shafiei et al. [196]. In this model, the vehicle attributes considered are purchase price, fuel consumption, length, luggage capacity, acceleration and two parameters, lower medium and upper medium. These parameters signify an agents attraction or aversion to a particular model based broadly on its perceived value for money. Some agents will prefer over-priced vehicles, largely for hedonistic reasons, whereas others will feel cheated. Studies by Axsen, Orlebar and Skippon [12] and Schuitema et al. [193] show that social influence, hedonic and symbolic vehicle attributes play a significant role in influencing purchase decisions; the Shafiei et al. model seeks to incorporate these attributes though the upper and lower medium parameters and agent knowledge of other agent's purchase decisions.

The ABM is constructed using consumer choice input data to parametrise the agent decision algorithm. This takes the form of:

$$P_{i,j,k} = \frac{W_{k,j,t}.\exp\left(\sum_{a=1}^{A} \beta_{i,a,t} \times X_{a,j,t}\right)}{\sum_{j=1}^{V} W_{k,j,t}.\exp\left(\sum_{a=1}^{A} \beta_{i,a,t} \times X_{a,j,t}\right)} \tag{2.2}$$

where:

$P_{i,j,k}$	Probability of purchasing vehicle j by consumer i at time t
$\beta_{i,a,t}$	Preferences of consumer i for attribute a at time t
$X_{a,j,t}$	Value of attribute a for vehicle j at time t
$W_{k,j,t}$	Willingness to consider vehicle j by drivers of vehicle type k at time t
V	Number of vehicles
A	Number of attributes for vehicles

W typically starts at zero where k represents a BEV but would be 1 where k represents a ICE vehicle. W in respect of BEVs can be increased through marketing, social exposure and direct word of mouth and indirect word of mouth. However, W can also decay over time if the agent does not purchase a BEV.

Following the work of Schwoon [194], Shafiei et al. also incorporate a modifier to the probability estimated in equation (2.2) to take account of refuelling and range inconvenience associated with EVs. This takes the form:

$$\bar{P}_{i,j,t} = \frac{P_{i,j,t} \times RFE_{i,j,t}}{\sum_j P_{i,j,t} \times RFE_{i,j,t}} \tag{2.3}$$

The refuelling effect, RFE, is a function of social acceptability and driving patterns:

$$RFE_{i,j,t} = \begin{cases} 1, & j = \text{ICE} \\ 1 - DP_{i,t} \times e^{-\alpha . S_t}, & j = \text{EV} \end{cases} \tag{2.4}$$

where:

$RFE_{i,j,t}$	refuelling effect for consumer i using vehicle j at time t
$DP_{i,t}$	Driving patterns of consumer i at time t
$S_{j,t}$	Availability and social acceptability of charging facilities at time t
$\alpha > 0$	Scaling parameter used to calibrate model

This study does, however, assume that consumers are able to perfectly calculate the economic utility value (equivalent to Total Cost of Ownership, including depreciation (TCO)) of different options and make purchasing decisions based on such assessment. Importantly, the model also removes vehicles from the model when a new vehicle is purchased, so there is effectively no used vehicle market. This is clearly problematic since the majority of vehicle purchases are of used vehicles (in the UK, vehicle owners keep their vehicles on average between 2 and 3 years but the vehicle itself lasts about 15 years [226]).

Sullivan, Salmeen and Simon [208] developed an ABM to predict the penetration of PHVs. In their model they include four classes of decision making agents; consumers, government, fuel producers and vehicle manufacturers/dealers. Each of these agents interacts on a monthly basis; consumers consider a possible car purchase and have a choice (from manufacturer agents) of 12 different models from three manufacturers, those manufacturers replenish and adjust pricing based on demand. Governments review progress against targets, and may change policies accordingly, whilst fuel suppliers adjust prices based on exogenous factors and competition between fuel types. They validated the early years of their predictions against actual US PHV sales data. Other aspects of the model are validated only in so far as the emergent behaviour follows expected norms; for example, the penetration of PHVs follows a 'S' diffusion curve and a vehicle manufacturer reducing the cost of their cars results in greater sales.

A similar, but more recent, study by Adepetu, Keshav and Arya [1] in 2016, focuses on San Fransisco. Their consumer agents also include a 'greenness' variable to represent a person's tendency to incorporate lower carbon footprint into their purchase decision; greeness is correlated to income with greater variability in greeness at high incomes and lower income groups having lower greeness (more cost focussed). This model also incorporates a function representing the ability of individual agents to accurately estimate TCO of vehicles and thus the relative benefits of lower running costs (for EVs) vs lower initial capital cost for conventionally fuelled vehicles. The study adds temporal and spatial information to enable the impact of charging station location to be considered and, on the assumption that there is immediate un-controlled charging when available, predicts the impact on electricity demand at various locations in the city. Adeptu et al. note that large EV batteries significantly reduce the need for public charging stations, which could have longer term impacts on the importance of day-time V2G in influencing EV purchase. Eppstein et al. [82] add further social influence in their ABM, which focuses on PHVs, through a parameter designed to adjust individual agent's susceptibility to media and to their social network, which is selected based on homophily criteria with other agents. The model also assumes that some owners make rational assumptions of fuel costs whilst others do not, thus reducing the reliance on an accurate TCO in the decision making process. For simplicity, the model assumes uniform daily driving patterns and assumes daily recharging is always available. This degree of simplification is unlikely to be suitable for pure battery-electric vehicle (BEV) adoption given the additional range anxiety and need for charging infrastructure. Krupa et al. [128] confirm this in a consumer survey focusing on PHVs in which 77.8% of respondents noted that electric driving range was not limited unlike that of a BEV; despite this, study participants reported that the availability of public recharging infrastructure would have a positive influence on their purchase decision. The study also notes that the value of future fuel savings is probably insufficient to persuade most consumers to pay the additional up-front cost and that rational financial analysis is rarely applied to vehicle purchase decisions. Indeed, whilst the survey response indicated some 69.7% regarded seeing other similar vehicles on the road as having no influence, later questioning indicated that participants would only consider a purchase after PHVs had reached a certain level of penetration, suggesting social influence is important. Vehicle segment was also found to be important, with larger drivers generally unwilling to trade down where PHVs were not available in the same segment as their existing vehicle.

Many of these models take an ad-hoc approach to modelling consumer behaviour, with various rules being added to cover different aspects, such as greeness [1], susceptibility to peer influence [82] and TCO calculation ability [1]. Jager, Jannssen and Vick [116] put forward the '*Consumat*' model of human behaviour in 1999, bringing together various theories relevant to understanding consumer behaviour; this approach goes someway to formalising a means to model human behaviour within the ABM environment. A *Consumat* is an agent that participates in four processes; deliberation (e.g. assessment of utility of an EVs purchase), social comparison (e.g. am I as green as my peers), imitation (copying peers) and repetition of previous actions. The objective, as always with an ABM, is to understand how the micro-decision making processes of the *Consumats* impact on the macro-scale results; in this case, the diffusion rate of EVs. Jager et al. [116] went on to demonstrate the use of the *Consumat* model in a 'commons dilemma' in which multiple agents seek to optimise the outcome across all agents where there are limited and conflicting resource requirements and as such individual optimisation does not result in overall optimisation. Although not directly related to uptake of EVs, there are elements of commonality in the environmental aspects of EV purchase decision making. The *Consumat* model was further updated by Jager and Jannssen in 2012 [117], this introduced variability in the capability of agents to, for example, assess the utility of a purchase decision and slightly changed the original processes.

Kangur et al. [121, 122] have developed an agent based simulation for diffusion of EVs, known as 'Simulating the Transition to Electric Cars using the Consumat Agent Rationale' (STECCAR) based on a *Consumat* model. Figure 2.4 provides an overview; *Consumats* are car drivers who each week evaluate their four needs (financial, functional, social and environmental) against the performance of the vehicle. The primary focus is to satisfy financial and functional needs, but where possible to optimise social and environmental needs. Each agent has a different set of personal attributes which determine whether the agent is satisfied and certain. Here 'Certain' means that they are comfortable in their mental state, for example, in regard to how they fit into their social group. It is measured by calculating a variance between the owner's needs measures and those of their peers. The evaluation of needs and mental state results in four different agent conditions. A satisfied and certain agent will keep their existing vehicle, a dissatisfied certain agent will gather information about vehicles in the market and make a purchase if a suitable vehicle is available. A satisfied, uncertain agent imitates others in their

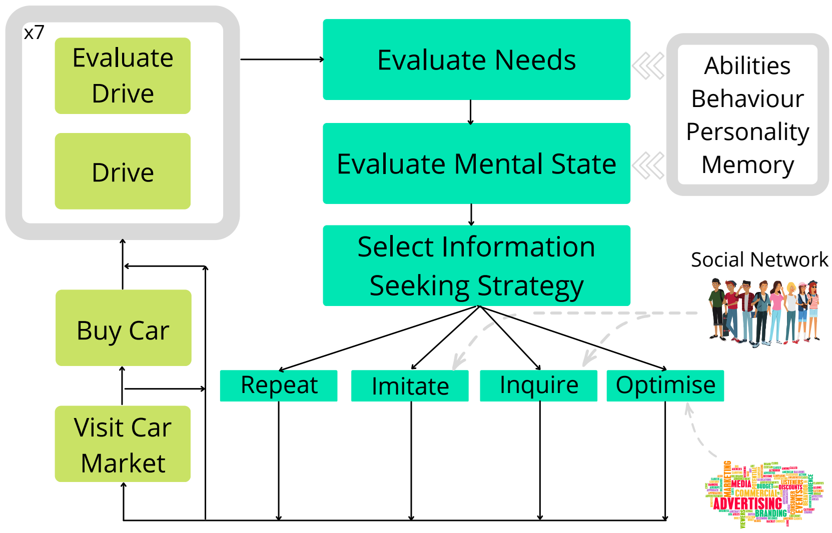


Figure 2.4: Overview of STECCAR model showing drive cycle output interacting with *Consumat* model to drive vehicle purchase decision [121]

social network, a dissatisfied, uncertain agent will both consider vehicles owned by others in the social network and those available in the wider market; agents in either of these states may or may not purchase a new vehicle.

The STECCAR model is interesting in that it evaluates purchases of the three main car groups (ICE, BEV,PHV) and allows agents to purchase vehicles from the used car market as some owners dispose of their vehicles. The authors have also validated the model against a number of market metrics including the rate of turnover of vehicles (used car market), duration of vehicle ownership, average vehicle age and market penetration. The model performs well on the first three of these, but tends to over estimate market penetration compared to the limited sales data available; 0.064% vs 0.22% BEVs and 0.4% vs 0.83% PHVs.

UK EV adoption forecasts

Whilst there are numerous studies exploring aspects of AFV adoption, often focusing on barriers, there are few that attempt to forecast adoption at a country level. The only recent academic study forecasting EV adoption in the UK is that by Rietman, Hugler and Lieven [187], which covers 26 countries in total using a logistic growth model. Equation 2.5 sets out the growth function employed.

$$I(t) = \frac{L}{1 + \left(\frac{L}{I(0)} - 1\right).e^{-kLt}} \tag{2.5}$$

where:	$I(t)$	=	inventory at time t
	$I(0)$	=	inventory at start
	L	=	saturation limit
	k	=	growth factor

This forecast relies on data from a few years of very low EV penetration combined with expectations of full adoption to generate a suitable 'S' curve. Whilst it implicitly takes into account historic policies and is rate limited to historic vehicle turnover rates, it cannot take account of any future changes to such policies, nor can it account for aspects of EV adoption that may differ from conventional technology adoption; for example, range anxiety and the relationship between charger availability and willingness to adopt. The analysis also assumes continued growth in car ownership, with some 38.4M cars on the road compared to 31.9M today [226]. It remains unclear whether car ownership will continue to grow or, indeed, whether there may be a shift to MaaS as forecast by National Grid Company (NGC) and others. Rietmann et al. go on to explore the carbon savings delivered by EVs, however, they assume a constant grid emissions intensity at 459gCO_2e kWh^{-1} (note e indicates CO_2 equivalent and includes other greenhouse gases adjusted to a CO_2 base for warming impact), which is claimed to be a 2018 figure, but which appear closer to emissions in 2015; according to UK Government sources, the UK emissions coefficient was 283gCO_2e kWh^{-1} in 2018, see Figure 3.3 sourced from UK reporting statistics [221].

NGC uses four scenarios to forecast future electricity system demands as illustrated in Figure 2.5. The impact of these scenarios on EV adoption is shown in Figure 2.6. In the 'steady progression' scenario, there is slower adoption of EVs and they continue to be used as primary transport for most journeys, in the 'system transformation' and 'consumer transformation' scenarios there is some modal shift to autonomous vehicles such that that there are fewer multi-car families. In the 'leading the way' scenario there is a significant societal shift towards autonomous vehicles and public transport and many homes opt to have no car at all. This shift towards MaaS presents a challenge for modelling EV adoption since it represents a significant societal shift that requires a much more sophisticated approach to human behaviour modelling than those presented to date. Furthermore, to forecast charging demands becomes more complex in such situations

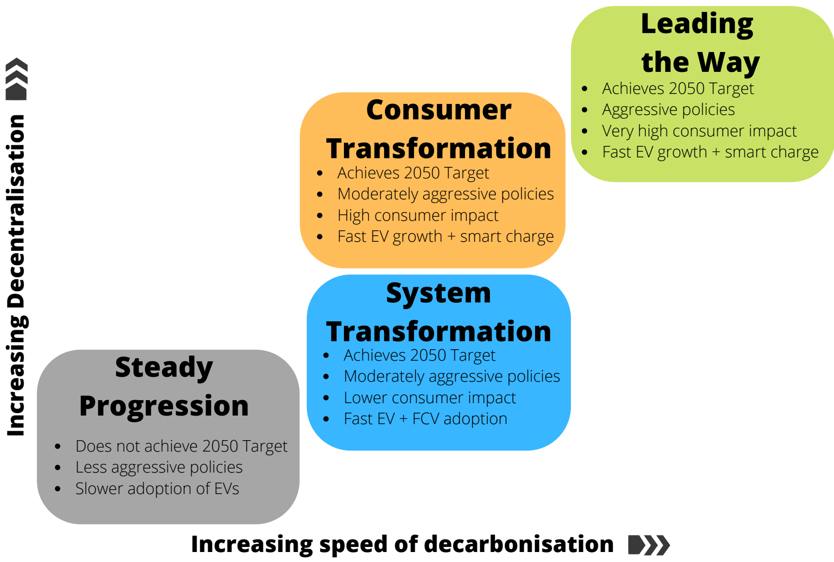


Figure 2.5: Future energy scenarios from NGC [157]

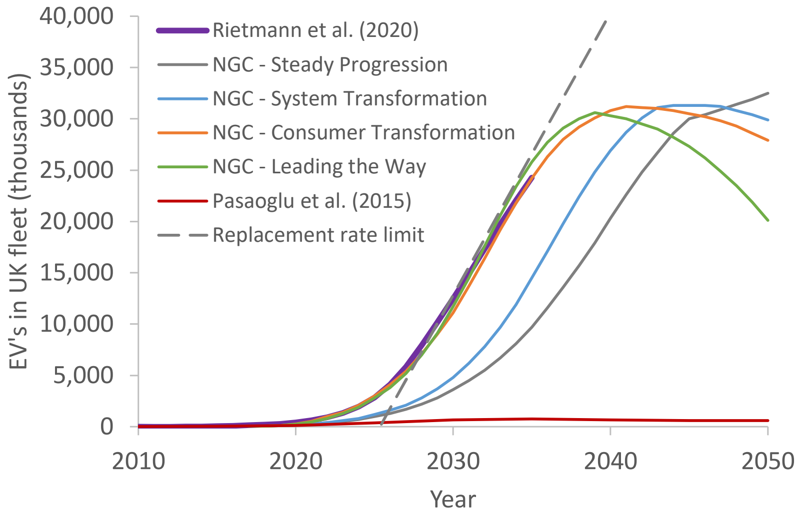


Figure 2.6: Comparison of UK EV adoption forecasts presented by [157] and [187]

since vehicle utilisation and charging availability windows are likely to be different to those with privately owned cars. The Rietmann et al. analysis indicates very similar adoption levels to those of the more optimistic NGC scenarios although it should be noted that in none of the latter is there any significant increase in total vehicles in the fleet, thus as a percentage adoption, Rietmann et al. is forecasting somewhat lower adoption.

Figure 2.6 also plots a realistic maximum rate at which the market can change based on the highest rate of new car additions to the market between 2005 and 2019. Whilst it is possible that demand for new BEVs will exceed historic sales rates, in seems unlikely that this limit would be exceeded to any significant extent without costly policy intervention since it would require both increased EV manufacturing c.f. ICE vehicles and extensive early scrappage of existing vehicles. The most rapid adoption rates shown here match, but do not exceed, this hypothetical limit suggesting that EVs dominate car sales in the late 2020s to early 2030s in these forecasts.

An earlier study by Pasaoglu et al. [180] in 2016 sought to use a systems dynamics model created in an agent environment to model the key actors in power train transition at a country level across the EU. The model uses agents, but these are restricted to a single agent to represent each of the actors; consumers, manufacturers, governments etc.. Whilst the model takes into account many of the key interactions, it is perhaps a salutary lesson in forecasting; the results indicate that up to 2050, BEV and PHV sales(i.e. plug-in cars) remain at about 8% of car sales. Given that the replacement rate is around 8% of the fleet each year, the total numbers stabilise at about 2% of the car fleet. However, by the third quarter of 2020 European Automobile Manufacturers Association (ACEA) reported that sales of PHVs and BEVs were at 9.9% across the EU, compared to a Pasagoglu et al. forecast of 3.5%. Note that the study does not forecast the fleet composition, but rather the fraction of sales of each power train; the number of EVs (BEVs and PHVs) presented in Figure 2.6 is estimated assuming that new car additions of each powertrain become disposals at an average of 15 years after first sale.

2.4 Validation of ABMs

Given the previously acknowledged challenges regarding the opaqueness of ABMs and difficulties in validation, it is important to consider approaches that can support a greater degree of confidence in the model outputs.

Windrum et al. [237] noted the two different approaches of 'realism' or 'instrumentalism' and that the latter may not capture the effects of different policies and technologies. As such, the most appropriate strategy to meet the objective of this study is to adopt a more 'realist' approach, which of itself tends to result in a more opaque and complex model. Windrum et al. identify three different approaches to applying empirical validation of such models:

Indirect Calibration Approach This is a four step process:

1. Identification of 'stylised facts' that the model is intended to reproduce or explain; these are typically macro-level observations.

2. Model construction such that the micro-level functionality closely matches behaviours and interactions at the micro level.

3. The initial conditions and parameters of the model are restricted so as to reproduce the macro-level observations and subsequent analysis is then restricted to only those parameter combinations that maintain the macro-level output.

4. In a final step, further analysis of the causal mechanisms should be undertaken and any new stylised facts explored which the model can validate *ex post*.

The Werker-Brenner Approach This approach was developed by Brenner and Werker [236] and uses a three step process:

1. Existing empirical knowledge is used to calibrate initial conditions with wide ranges applied to those parameters where knowledge is sparse.

2. The outputs from runs of the model using the parameter ranges in step one are validated against empirical data and only those sets consistent with current known data are retained.

3. Referred to as 'methodological abduction', the remaining model sets are explored, potentially with the aid of expert testimony, to identify the combination most likely to represent the real system.

The History-Friendly Approach This technique aims for a more concretised approach, attempting to isolate key causal mechanisms and reduce model complexity to the point where, whilst still replicating real-world decision processes, the model can be shown to reproduce historical trends and observations. This enables a strong quantitative analysis of the model outputs, but clearly can only be applied rigorously where reliable historical data sets are available.

The case of EV deployment is interesting in that studies [128, 193] show many underlying purchase motivations remain consistent with those of ICE buyers; for example, car segment, hedonistic aspects, performance, economy and cost. But in addition, new features such as range and charging availability become significant and emissions performance may be a key driver for some purchasers. Furthermore, the deployment of BEVs is currently very low (<1%) and thus whilst some historical data exists, it is probably insufficient to validate the model.

However, there is extremely robust data available for the transition from petrol to diesel vehicles and a small quantity of data for HEVs and PHVs in addition to BEVs [226]. A critical difference between HEVs/PHVs and BEVs is that the former do not incur range anxiety issues, which are known to be of concern to BEV adopters [92, 153, 165]. Thus in validating an EV adoption model, a mixed approach to validation may be appropriate; combining aspects of the history-friendly and indirect calibration approaches.

2.5 Policy impacts on EV adoption

A large body of research exists around the impacts of policy and incentives on EV adoption. Historically, policy analysis regarding shifting to lower emission vehicles has frequently focused on the relative merits of fuel taxes vs purchase incentives. Grigolon et al. [104] explore how consumers value fuel costs and tax policy through an analysis of European vehicle sales. This work focuses on diesel vs petrol, exploring inter alia, the extent to which consumers are willing to pay more for a diesel car in order to reduce operating costs through greater efficiency, and thus lower emissions. The analysis suggests that consumers are rather effective at determining the cost benefit of higher purchase costs vs future reduced fuel costs, yet this is somewhat at odds with other work both in the general field of energy efficiency investments where the 'Energy Efficiency Gap' [97] is thought to be caused, in part, by the failure of consumers to properly consider TCO. Indeed, a study by Dumortier et al. [71] suggests that consumers decisions are uninfluenced by stating fuel cost savings over five years, but giving more accessible TCO information, in the form of 'Energy Performance' type labels does help persuade drivers of smaller vehicles, perhaps reflecting those more likely to be concerned with operating costs, to consider AFVs. Nixon and Saphores [163] found that a $1,000 increase in purchase price needed to be offset by a $300 increase in savings on 12,000 miles driven, suggesting a simple payback evaluation of 3 years. Many econometric studies regard this as a myopic discount rate when analysed against a typical 10-15 year vehicle life, but this fails to take into account the practical ownership duration of vehicles, which in the UK has fluctuated between 2 and 3 years [226]. Thus in practice purchasers may be discounting the savings over their expected ownership duration. These studies also frequently consider purchasers as private vehicle users; fleet purchasers (for company vehicles) are likely to be more rigorous in their TCO evaluation than many private buyers. Thus it might be hypothesised that in countries, such as the UK, where a significant proportion of new cars are purchased by fleet operators (some 50% according to [199]) TCO will impact more heavily on new purchases and therefore the pool of used vehicles available at a later date. From this it could be inferred that, in the UK market, policies delivering the best overall TCO over a fleet lease duration might be best at encouraging the uptake of EVs whilst policies that reduce upfront costs may be optimal for private buyers.

An ABM study by Mueller and de Haan [154] looked more generally at how policies and incentives affect car purchase decisions. Whilst this study does not consider EVs, it employs a number of mechanisms by which purchase decisions are made and validates the aggregate output against real vehicle sales, showing good correlation. The correlation coefficients achieved for various vehicle parameters (CO_2 emissions, curb weight and rated power) vary from 0.726 to 0.863 depending on parameters used. The authors together with Scholz [51], go on to model the effects of feebates, which are policies combining rewards for good environmental performance and fees for poor performance, on consumer behaviour. In this work, they model overall cost-neutral feebate policies and show that these represent a suitable policy tool to drive energy demand reductions, but note that their efficacy depends on elasticity. Such policies, combined with commercial sector incentives from V2G contracts, could thus be a significant driver in the uptake of EVs.

Scrappage schemes, whereby an incentives is paid for owners of polluting vehicles to upgrade to cleaner vehicles, have been employed in a number of countries, principally following the financial crisis of 2008/09 [115]. Brand et al. [29] note that evidence of the carbon savings from scrappage schemes is scarce, with most having been introduced to invigorate the car market and not explicitly to reduce emissions. Such schemes need to be designed carefully to avoid perverse outcomes; the French scheme is thought to have encouraged more diesel vehicles with NOx effects being sub-optimal [115], and potentially worse impacts for particulate emissions, which were not analysed. Life-cycle carbon savings have not typically been included in these assessments. Brand et al. [29] suggest scrappage schemes may not be effective in reducing carbon emissions due to an increase in car use resulting from lower operating costs and higher emissions from car manufacturer and scrappage. However, more recent work by Craglia and Cullen [47] analysing extensive UK mileage and fuel price data between 2006 and 2017, suggests that British drivers are largely inelastic to fuel price and that improvements in vehicle efficiency are also likely to have little impact on mileage. Furthermore, in respect of life-cycle emissions, the Brand analysis (from 2013) assumes that the carbon intensity of electricity remains at a constant 400kgCO_2e kWh^{-1} to 2030, whereas UK electricity emissions had reduced to 233kgCO_2e kWh^{-1} by 2019 [107]. Similarly, Emilsson and Dahlof [79] found that, with improved metrics, their estimate of battery emissions fell from 150-200kgCO_2e kWh^{-1} in their 2017 analysis to 61-106kgCO_2e kWh^{-1} in 2019. The combined effects of these would almost certainly render scrappage schemes in a different light.

Nixon and Saphores [163] also identified that environmental impacts were not considered key; only 14% of respondents in their 2011 paper considered environmental impacts to be 'very important' when choosing a car, whereas all other factors included in the survey were rated in the 'very important' category by 32% to 66% of respondents. It was also evident that many respondents had little understanding of the relative environmental impacts of different cars, but that there was a significant correlation between education level and knowledge of environmental impacts. Anable [6] also establishes education as the only demographic variable that distinguishes members of groupings designed to reflect desires to switch transport mode to less environmentally damaging alternatives. Morrison and Beer [151] identify that environmental awareness is at a maximum during middle age, which may fit well with EV purchasing ability. However, the YouGov 2019 'Top Issues' survey [198] revealed that environmental concerns were ranked in the top three issues by 27% of the general population and 45% of 18-24 year olds, suggesting that the next generation of cars buyers will be significantly more environmentally aware. Thus it may be inferred that policies aimed at increasing public knowledge and understanding of the relative environmental impacts of different vehicles, and perhaps a more general increase in environmental awareness could assist sales.

Ebue and Long [73] identified both range and charging infrastructure availability as significant concerns for potential BEV adopters. These two factors are interlinked in that lower range vehicles require more charging infrastructure to provide worry-free driving. However, whilst range is a function of manufacturer development and consumer choice, the availability of charging infrastructure is not. Notably, Tesla identified this as a key issue and are the only manufacturer to have invested in their own network providing access to en-route charging for their owners; anecdotally, this is frequently cited as a reason to purchase a Tesla over other makes. Bailey et al. [17] notes a weak but significant link between knowledge of multiple chargers and interest in EVs, but this study was conducted in 2015 and included hybrids, for which en-route and other public charging is less critical. Bruckmann and Bernauer [31] surveyed Swiss drivers to establish preferences for pull (e.g. subsidies) and push (e.g. taxes) policies, whether knowledge of subsidy funding sources was significant and how current EV drivers differ from non-EV drivers. The hypotheses being that pull-type policies would be more attractive than push polices, knowledge of funding sources would diminish that attractiveness and EV drivers would be more supportive of both types than non-EV drivers. The results showed a clear preference for improving charging infrastructure amongst both EV and non-EV drivers whether or not the source of funding was known. The final hypotheses was shown to be true, with EV drivers generally more supportive of pro-EV policies. These findings suggest that there is scope for more aggressive push type policies and that public funding of charging infrastructure is likely to be well supported across all groups. Whilst early studies suggested a weak relationship between EV charger knowledge and EV interest [17, 197], this may have been the result of potential early adopters considering BEVs as being suitable only for short journeys and with home charging. More recent surveys [54, 55, 233] place infrastructure availability as an important factor in limiting adoption, typically behind range and cost.

2.6 EV grid services analysis and modelling using ABMs

There have been many studies exploring the impacts of EV charging on distribution networks; from those using simplified assumptions about journey completion times, with some stochastic analysis overlaid [175] through averaging of travel survey data [114] to the use of agent based models (ABMs) generating their own probabilistic travel patterns based on survey data [174, 212]. However, charging studies to-date have not taken into account the socioeconomic status of locales within the network, identified as a relevant in the 'Customer-Led Network Revolution' project [19], and have not implemented EV adoption models to any great extent, relying instead on assuming various levels of penetration. There have been relatively few studies investigating consumer willingness to participate in V2G or similar programmes [202]. This would seem to be a significant omission given the availability of capacity from EVs will, unless made compulsory by governments, be entirely dependent on consumer engagement.

Consumer choice in regard to EV range, and the balance between BEVs and PHVs during the adoption of AFVs, is important in that it will significantly influence the total storage capacity that could me made available for grid services. PHVs in particular, with their limited battery capacity of typically around 10kWh suitable only for a normal daily commute, are unlikely to be able to contribute significantly to grid reserve capacity both due to the limited storage and reluctance by owners to relinquish control over an essential element of their purchase decision [16]. Early phase adoption of both EVs and V2G will require consumer knowledge of the choices and products available; a 2017 Canadian study by Axsen et al. [14] showed confusion in regard to different types of AFVs and a complete lack of knowledge in regard to V2G; clearly there are significant knowledge barriers to overcome.

Parsons et al. [179] used a stated preference survey to gauge willingness to pay for V2G EVs in the US. The survey started with a choice between ICE and EVs of differing types/ranges and proceeded to introduce the concept of V2G and associated contracts. The contracts comprised various combinations of 'Minimum guaranteed driving range' (GMR - a minimum charge level), 'required plug-in time per day' (RPT), an annual cash-back payment or a reduction in the initial purchase price of the EV where a V2G contract is attached to it. The study identified that consumers perceive a high inconvenience cost associated with V2G contracts and that a high level of incentive was required to make such contracts attractive; these ranged from $2,368 per annum where the GMR was 75 miles and RPT 5h to $8,622 per annum for a GMR of 25 miles and RPT of 20h. Up-front discounts for the same cases were $4,252 and $16,628 respectively. However, it is worth noting that these GMRs are based on the maximum range capability of EVs existing at the time (the maximum being 200 miles at a premium of $24,000 over the consumers preferred ICE vehicle). Given the increasing range capability of EVs, an increased GMR of 100 miles may be quite reasonable and could significantly influence the results.

Bailey and Axsen [16] investigated acceptance of utility controlled charging (UCC - essentially charging and/or full V2G controlled by a third party) for those likely to be early-mainstream adopters of EVs, including hybrids, in Canada. Their study aimed to characterize consumer attitudes, quantify consumers preferences for enrolment in, and anticipate how consumers might respond to, differing UCC programmes by means of a stated preference survey. 53% of respondents indicated that they would voluntarily enrol in a UCC programme, but it is worth noting that environmental performance is more likely to be a concern in these groups and this study presented options where UCC specifically enhances renewable generation. Key concerns were in regard to privacy (24%) and loss of control (38%). Worries in regard to privacy are particularly interesting given more general privacy concerns around the internet and social media that have increased in recent years; this is an area which may be difficult to address adequately for an increasing number of consumers. Extrapolating to the broader population (as opposed to early-mainstream adopters), the authors estimate uptake of V2G without incentives to be about 22%.

In their 2016 paper, Axsen, Goldberg and Bailey [13], the potential for future EV drivers to respond differently to early adopters, or pioneers, is examined. This study reveals that pioneers are more likely to require higher compensation and guaranteed charge levels for participation in V2G schemes. Whilst the authors acknowledge this may be because pioneers have a greater understanding of driving needs, it may also be that they have been used to driving EVs with smaller batteries than potential adopters would consider. Pioneer adopters also value charging with renewables more highly than early mainstream adopters and thus careful design of V2G offers may be persuasive to this group.

2.6.1 Value of vehicle-to-grid to consumers

Estimates of net revenue from the provision of various grid services vary widely in the literature; in many cases this is because studies are undertaken in different markets which have different types and costs for grid services. National Renewable Energy Laboratory (US) (NREL) have reviewed the critical elements of V2G economics [205] and present some net revenue estimates for regulation services (frequency response), ranging from \$143 EV^{-1} year $^{-1}$ to \$3,320 EV^{-1} year $^{-1}$ and reserve services, ranging from \$31 EV^{-1} year $^{-1}$ to \$545 EV^{-1} year $^{-1}$ across a number of markets. Whilst the value of regulation services is significant, it is also the case that there is limited demand for such services and thus the value is likely to diminish rapidly with increasing V2G response volume.

Kiaee, Cruden and Sharkh [125] estimate the cost savings to consumers through participation in a car park V2G scheme based on energy arbitrage in the UK market. This analysis used UK balancing mechanism historic price data from a 5 day period in November 2013 and indicates a saving of 13.6% on the cost of charging without V2G. Given the relatively low variable cost of EV use, it is perhaps unlikely that a 13% saving, amounting to about £40 per annum at a retail price of 14p kWh^{-1}, would be attractive to many consumers.

2.6.2 Contribution of electric vehicles to grid services

There have been a large number of technical studies looking at the variety of services that V2G could provide. Sovacool et al. [202] carried out a systematic review of V2G studies in 2018. This work was mainly focused on identifying neglected areas, in particular social areas, but also identifies a range of recent technical work. The review considered some 197 papers published between 2015 and early 2017. Some 42% of papers discuss the link between V2G and renewable energy, whilst 24% specifically investigate the provision of transmission system services (such as frequency control). Smart grids are addressed by a further 17% and distribution services (such as local voltage support) by around 15%.

The main focus of this work is to identify the contribution that V2G can make to renewable generation balancing at a national level and within socioeconomic groups and over time scales of days and weeks. As such, this section of the review focuses on non-microgrid arbitrage related work; there are fewer studies focussed in this area than in the provision of grid services or micro-grid support.

Wu et al. [239] reviewed driving patterns in Denmark with a view to establishing the available capacity in EV batteries at different times of day and days of the week. This study is interesting in that it provides a similar summary of usage to data available from the UK National Travel Survey [223] and shows that very similar travel patterns exist, with a preponderance of short-distance journeys, an overall average daily distance of 29.48km (c.f. UK at 35km), and 'parked-availability' of over 94% during the day and 98% at night. This study does not go on to consider how this capacity might be used.

Udrene and Bazbauers [215] considered how V2G could contribute the Latvian power system. They considered a future EV population of under 1 Million and a relatively small average battery size of 30kWh, but nevertheless show that 247MW of peak fossil capacity can be avoided (the peak power demand in Latvia is just 1,368MW [83]). Interestingly, they also note that EVs have a significant impact on the operational mode of Latvia's combined heat and power plant; requiring more condensing operation in summer months and less in shoulder months. With high penetration of renewables, V2G makes a significant contribution to system balancing at times of low solar and wind generation, with up to 700MW being provided from EVs.

In a 2017 study, Noel et al. [164] simulated 86 million possible energy supply configurations for the PJM network in the US over a 4 year period at 1 hour interval to establish the most cost-effective energy supply arrangement taking into account environmental externalities. This work found that EVs used in V2G mode appeared in the most economically viable solutions, whereas stand-alone battery storage did not. However, this study uses a relatively simple approach to EV modelling, assuming that all EVs are connected in V2G mode when not being driven, and also assumes a connection capability of 10kW average per vehicle, which may be unattainable with a high penetration of EVs due to network constraints at a local level.

Hoogvliet, Litjens and van Sark [111] modelled the provision of regulating and reserve power from EVs in the Dutch Market. Although this study does not look specifically at how V2G can help support renewables penetration, it does consider short-term reserve markets (bid in 15 minute blocks up to one hour before real time to deal with supply imbalances) and thus might be reflective of a future market incorporating more variable generation. Their model takes into account EV journeys and State of Charge (SoC) requirements. EV users are divided into 3 categories: residents, who connect their cars only at home at night; commuters, who connect their cars only at work and resident-commuters, who connect both at home and at work. They use market prices to determine the value to the EV owner at between €120 and €750 per annum. They further consider the impacts on local networks showing that overloading and reverse flow on distribution transformers is possible with discharge rates between 3.7kW and 11kW per vehicle.

2.7 Transitioning away from personal transport

Decoupling of transport emissions from economic development is recognised as key to delivering sustainable growth [139]. Whilst electrification of personal transport is one element in this, a shift to greater use of public transport combined with its decarbonisation is also required, and has been a key element of policy in many countries. Tsoi, Loo and Banister [110] explored policies for emissions decoupling in 8 developed and 8 developing nations, finding that increasing public transport use was a key theme across many, including the UK in its 2009 'Low Carbon Transport Strategy' [63]. Whilst that document has now been withdrawn, the UK's "Future of Mobility: Urban Strategy" [67], notes that *"Mass transit must remain fundamental to an efficient transport system"* and that *"New mobility services must be designed to operate as part of an integrated transport system combining public, private and multiple modes for transport users"*. The UK Government also published a national bus strategy in 2021 [225], which includes a vision to bring 4,000 new green buses into service. The strategy notes a steep decline in local bus journeys outside of London following bus deregulation in 1985, with total journeys undertaken having fallen by nearly 50% since then. Moving passengers from personal transport modes to public transport has a number of additional benefits including lowering overall energy use per passenger-km (with sufficient occupancy), reducing congestion and reducing non-exhaust emissions such as tyre and road wear [52, 190], the later two being particularly important in urban areas and during peak demand periods.

Given the benefits of a shift to public transport, the need to manage electric vehicle charging demands and address issues of social equity in charging, exploring ways to make public transport more desirable and integrate more effectively with other modes of transport is an important area of research.

Past guidance on promoting public transport use [62] have focused on availability, cost and safety as the key barriers. However, Mann and Abraham [147] sought to explore less utilitarian considerations through a series of in-depth interviews. Some of the key findings were that a 'pleasant' journey was highly valued, that the sense of personal space maintained by car use was often relevant and for some users, the sense of identity provided by their car was important. These affective considerations played alongside the utilitarian issues, thus whilst absolute journey time may be important, creating a simpler and more pleasant experience may reduce its importance in the user's decision making process. Hine and Scott [108] explored the the issues of public transport journeys and interchange and note that users tend to select faster and more direct routes, with interchange offering no benefits other than potentially minimising journey time. They identify a number of findings that would lead to more attractive public journeys involving interchange including:

- Reducing the emotional burden of interchange (aspects such as information provision and security being important)
- Short walking distances of 5-10 minutes
- Minimisation of time pressures (frequent connections, ease of finding connections)
- Fair costs; it was noted that car users often understated the full cost of their journey, referring to running costs only
- Reducing the benefits of free parking at or close to work locations

Given the challenge of providing sufficiently frequent, yet cost effective, bus services in rural locations with few customers, the concept of a Park and Ride (PnR) commuter hub may be attractive. Such a hub would potentially reduce the number of interchanges required for a rural commuter and could also work alongside city traffic management plans and pollution zones to provide a fair, and cost effective, alternative for car users. Making use of modern electric and/or hydrogen buses would also overcome some of the issues raised in the studies here (such as interchange stations being 'smelly' [108], presumably referring to diesel). An appropriately located hub could also take advantage of renewable energy resources, particularly solar and wind, to provide low-cost energy for buses, helping to maintain a competitive cost vs. private cars. If such a hub could also provide cost-effective car-charging facilities, then this would be an extra attraction for car users, particularly those without access to home charging thus also helping to reduce social inequity.

PnR schemes have been in operation in the UK since the 1970s, but it has not always been clear on the extent to which they reduce traffic. Parkhurst [178] examines a number of PnR scheme studies and identifies some complexities in the use of such facilities, with some users switching from all-bus journeys to car plus bus for example. The study also questions whether overall urban traffic reduced as a result of the schemes or whether the capacity 'freed' by the PnR scheme was subsequently subsumed by traffic growth. Indeed, in a subsequent study, Parkhurst [177] examined eight PnR schemes and found seven reduced traffic in the urban area served, but that the main effect was to redistribute traffic rather than reduce traffic overall. Parkhurst concludes that PnR schemes cannot be operated in isolation, but need to form part of an overall strategy where policies to reduce car use in cities are introduced in parallel and that the location of PnR must also be considered in respect of the potential for perverse modal shift outcomes.

One question that might also arise in some areas is the potential for PnR schemes to operate bi-directionally; i.e. for the site to operate primarily for city destinations during working days, but for rural recreation destinations on non-working days. Such a scheme might give greater overall benefits in traffic reduction. The Peak District National Park represents a particularly suitable testing ground for such a concept since it has major commuting destinations, such as Derby, Sheffield and Manchester close to its perimeter and also experiences very high volumes of tourist traffic at weekends; some 22Million visitors per year, with 83% arriving by car [181]. Public transport within the park is fairly limited due to the dispersed nature of settlements and, provided that a PnR hub is not sited close to routes served by the Hope Valley rail line, it is less likely to result in perverse modal-shift outcomes.

Electric car PnR have been explored by, inter alia, Sohet et al. and Ai et al. [2, 201]. Ai et al. sets out a suitability index for EV charging locations, which are also appropriate for commuting or shopping trips, to be used as a planning tool. Schemes have been developed in some US cities including Los Angeles, Boston and New York, but are otherwise limited. An interesting observation from the New York sites is that the mean plug-in time is 7.6h, but only 2.1h are actively charging. This implies low charger utilisation, but also significant potential for demand management to match charging demand to periods of generation or to avoid peak demand charges/network reinforcement. Alternatively, it presents the possibility of managing those who choose charging spaces by requiring a minimum kWh charge, which could be delivered in practice by a connection fee which is effectively refunded above a set energy transfer. The study focuses on selecting suitable station-based sites on the metro system in Chicago. However, the factors included in the suitability index focus on EV ownership (current and future) and existing use of PnR facilities as well as area population growth and availability of parking space. As such, they do not address social equity issues and may exacerbate the situation by providing charging facilities in growth areas with high EV ownership, which are considered likely to be in higher income locations. As such, the index proposed does not appear suitable for all applications.

In their paper, Sohet et al. explore the integration of renewable power, solar PV, in combination with a parking hub in France. They develop a 'travel duration cost' function, see Figure 2.7, based on congestion effects from the number of drivers choosing to drive into downtown Paris versus using the PnR facility, based on the value of time when driving or on public transport from French government research. Actual fuel costs of driving or using the PnR facility are added to the perceived cost. Whilst the PnR cost is constant, the cost of charging is determined from an algorithm based on the number of cars charging and PV generation at the time. A challenge for this strategy is that EV owners can only estimate the cost of charging on any given day (or be provided a forecast by the charger operator). In the model presented, the alternative to PnR charging is to charge 'downtown' at a fixed cost of €0.40 kWh^{-1}. In practice, this seems a rather high price when measured against UK costs, which could vary from around €0.057 $^{-1}$ (Octopus Go, home off-peak tariff) to €0.25 $^{-1}$ (UK average public slow charger tariff - [75]). It seems likely that EV owners will have some awareness of their own charging costs and, unless planning a long journey, would be unwilling to charge at potentially higher prices than their norm.

These studies, in part due to the PnRs often being associated with metro-rail services, do not consider electric or hydrogen bus energy requirements. There is an extensive body of research on both types of low carbon buses, but this is focused primarily on energy storage systems, powertrains and energy management, with less emphasis on charging demand patterns [56]. Gao et al. [94] set out a methodology for using a neural network to estimate electric bus power con-

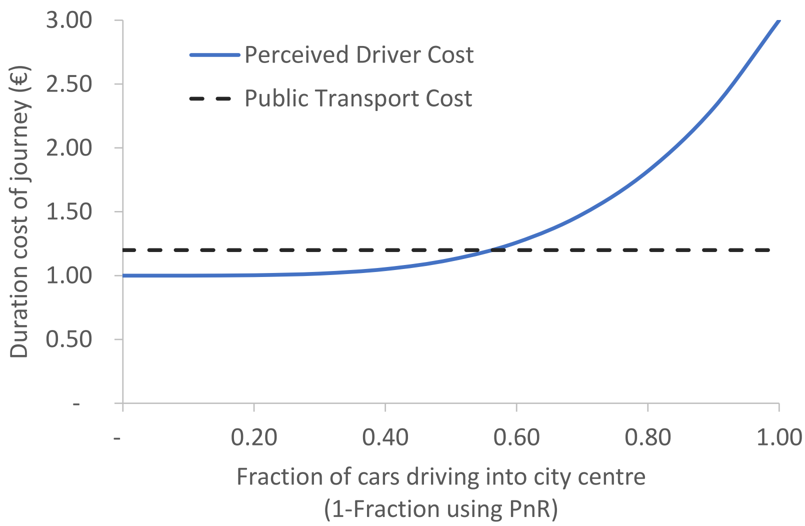


Figure 2.7: Perceived private car duration cost and public transport duration cost of commute from PnR to city centre [201]

sumption in varying weather conditions and thence optimise charging patterns to reduce expenditure on bus chargers as well as charging cost, which they estimate was reduced by 10% in their case study. Whilst their study establishes a useful methodology where detailed weather data and historic performance is available, it is not possible to apply the methodology to new routes without such data. Xylia et al. [240] assessed routes for electrification in Stockholm by optimising the location of chargers and available time for charging at specified stops. This study employed electric buses of very short range (60kWh battery implying around 45km of range, sometimes referred to as 'opportunity charging' models since they typically require day-time charging), but was still able to demonstrate benefits over diesel/biodiesel buses despite requiring the installation of on-route and destination chargers.

Göhlich et al. [100] set out various options for urban bus electrification, including bus form (single/double/articulated etc.), charging strategy (depot-based, inductive opportunity (on-route) and conductive opportunity) and battery chemistry (NMC and LTO, being able to charge at high C-rates and thus most suitable for opportunity charging and LFP, with a lower C-rate, suitable only for depot charging). They also highlight the importance of climate control within the vehicle based on past analysis by Göhlich et al. [99] where an economic assessment of various heating and cooling systems demonstrated annual electricity use of 5.16 to 11.8MWh and peaks of 18 to 30kW depending on system type (principally resistive vs. heat pump based systems). A TCO assessment [100] suggests that opportunity charging approaches using smaller, lower cost, batteries with frequent high-rate charging are expected to return lower operating costs than depot charging solutions in 2025. With the later having a higher mean cost than diesel. However, the vehicle acquisition costs for this study indicate a 300kWh depot-charging bus at €515k (£450k) in 2021, whereas quotes from a UK bus supplier for an NMC 385kWh bus suggest £400k, further illustrating the rapid decline in battery costs. Whilst costs for other chemistries may also have declined, the relative costs of batteries vs. on-route charging points will play a role in the cost-effectiveness of different options.

Jefferies and Göhlich [119] go on to present a comprehensive simulation incorporating charging infrastructure optimisation and bus scheduling, building on the TCO work described previously. The analysis is split into stages, with the first stage taking a bus timetable and applying a scheduling algorithm to determine the number of each type of bus required. Schedules are then joined to maximise the length of each bus service-cycle within range capabilities and taking into account opportunity charging. This results in bus-specific schedules which are subsequently operated in a schedule simulation stage, incorporating heating and cooling demands, which generate energy demand profiles, driver requirements and depot requirements. Costs are applied to these outputs to generate a TCO for the scenario modelled. One shortcoming of this approach is that it cannot make adjustments to route schedules to take account of different weather patterns (resulting in different energy consumption) or reduced State of Health (SoH) of the vehicle battery over time since buses operate the same schedule throughout the simulation. An interesting feature of the work is the use of a 'pre-simulation' genetic placement optimisation process for opportunity chargers using a simplified TCO approach to reduce computing time; this establishes a cost-optimised set of charging locations which are fed into the main simulation. One practical consideration here is that the suitability of locations for chargers will depend on the availability of grid infrastructure and space constraints. It seems likely that in practical applications, these features will dominate and thus opportunity charging locations may, to a large extent, be pre-determined.

In a study of sustainability of fuel cell buses, Lozanovski et al. [144] show that buses fuelled from grey hydrogen (manufactured from natural gas) exhibit higher life-cycle emissions, on average, that an equivalent diesel bus, but that a green hydrogen bus (from renewably powered electrolysis) has substantially lower emissions; under 250gCO_2e km^{-1} at 720,000km compared to 1250gCO_2e km^{-1} for a diesel bus and ca. 1380gCO_2e km^{-1} for grey hydrogen. Thus ensuring that hydrogen buses are fuelled with clean, green, hydrogen is essential in delivering climate mitigation benefits. Cockcroft and Owen [45] cite lower, operational only, emissions for green hydrogen of 95-100gCO_2e km^{-1},with similar figures for diesel buses, but go on to reinforce the benefits of hydrogen buses (applicable also to electric buses) through a comparison of other exhaust emissions. However, they conclude in this 2014 study, that the high purchase cost of hydrogen buses renders them noncompetitive against diesel technology.

These studies therefore suggest that, where feasible, onsite renewable power able to generate at least part of bus demand, whether electric or hydrogen, could offer both better sustainability and lower cost. There is little analysis in the current literature in this regard, perhaps since most focus on urban locations where on-site generation opportunities are limited. Where research does exist, such as Arif et al. [9] and Zhuang et al. [243], they tend to focus on optimising charging patterns in association with on-site battery storage to minimise peak demands and, in the case of Zhuang et al., to reduce charging costs by also utilising the electric bus battery as bi-directional storage. Whilst the later seems laudable, given the limited time that electric buses are in-depot, particularly in combination with high solar output as modelled here, and the need for full recharges each night, practical applications are likely to be limited.

The concept of a PnR and combined bus depot facility in an edge-of-town location with the potential for on-site renewable generation, operating in a bi-directional mode is, as far as the author can determine, a subject as yet unstudied.

2.8 Conclusions

The literature reveals studies evaluating the uptake of EVs in a number of markets and using various methods, however, there is lack of UK-focused EV growth studies and little research into socioeconomic aspects of EV adoption. Agent based approaches have been shown to be effective in modelling the growth of EVs elsewhere and, in particular, have been validated against those subsets of EVs where sufficient market data exists. The technical potential of V2G to support networks with high renewables penetration has also been investigated extensively. However, social dimensions of EV adoption and use patterns and how such factors affect the availability of V2G resource are largely unexplored. Without a better understanding of these issues, determining a realistic contribution of EVs and V2G to the provision of network services is not possible. Car owners are known to be influenced by social networks and peer pressures; agent based simulation has been successfully deployed to model such social interactions. Thus agent based multi-scale modelling would appear to be an appropriate approach to tackling the gaps present in the current literature.

The need for modal shift to more public transport has been widely recognised, but in parallel, it is clear that EVs, with their low operating costs, could make for even greater challenges in achieving pubic acceptance of that need. Providing clean, low cost and easy to access public transport, whilst also giving consumers the additional benefit of car charging whilst their vehicle is parked, could help facilitate greater public transport adoption. This concept has not previously been fully explored from a technical perspective and is also considered an appropriate candidate for multi-scale agent based modelling. This can enable an exploration of the economic viability of a public transport hub powered by its own renewable energy sources and its impact on helping to reduce social inequity in EV charging.

Chapter 3

Methodology: Behaviour-based EV adoption and grid integration model

This chapter sets out the methodology employed in the BEVI model. The model has been built in Anylogic, a proprietary ABM environment. The first section provides a brief summary to enable the reader to obtain an overview of how the model is assembled. This is followed by detailed descriptions of the data sets and their application, algorithms and other functionality grouped by agent type as illustrated in Figure 3.1.

3.1 BEVI model overview

BEVI is an ABM incorporating a diversity of interacting agents with complex rules able to replicate many social interactions, driving and charging behaviours alongside the technical capabilities of vehicles. The key outputs from the model are adoption rates and fleet composition and charging demand patterns at half-hourly resolution. Importantly, these can be dis-aggregated to a number of geographically-based social groups and income bands. The model is comprised of the components illustrated in Figure 3.1. In this opening section, the scope and main data sets used in the simulation are described together with an overview of the key functionality. The following sections describe, in detail, the functionality of each agent class in the model.

The BEVI model combines human behaviour modelling, using a *Consumat* approach, with the uptake of AFVs and includes elements of behavioural modelling within individual agent charging strategies to generate a more realistic set

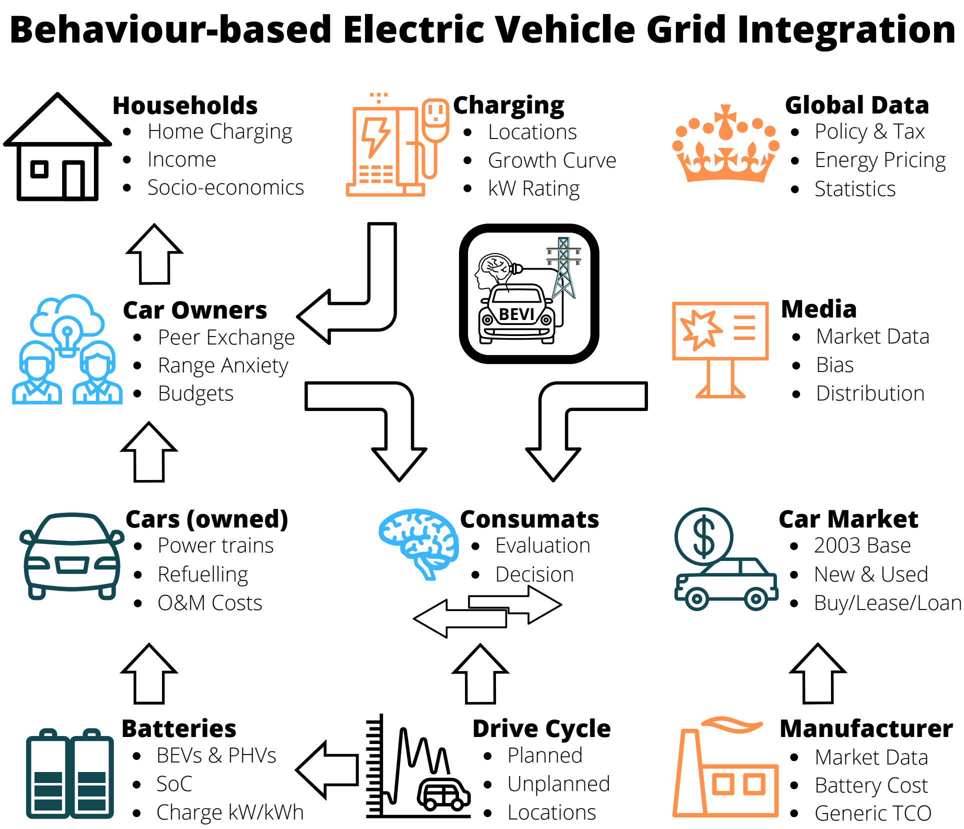


Figure 3.1: Overview of model structure showing agent populations and main interactions. Blue icons represent human actors with decision functions and multiple agents, green icons represent inanimate actors with decision functions and multiple agents, orange icons represent institutional actors that follow historic data sets and generate future model data. Car owner agents belong to household agents and hold household level data such as income and charging availability. Home-based charging patterns and socioeconomic statistics are also collected at this level. Drive cycle data, extracted from the National Travel Survey, determines car owner journey's, battery (and fuel) use and informs range requirements used by *Consumats* to determine minimum range criteria.

of charging profile data. The model employs travel survey and car fleet data of a nature produced by many national governments and industry bodies; here data applicable to the UK is used. More specifically, the travel data employed is from the National Travel Survey for England only. Within the model, six different multi-agent types are employed as follows.

- Cars: initialised as a set representative of the 2003 UK vehicle fleet. The car agent performs all technical car functions such as determining efficiency, breakdown frequency, fuel consumption and operating costs and also maintains knowledge of the car location for EV charging purposes. (ICE cars are assumed to be able to refuel at any time.)

- Batteries: battery agents may be considered an extension of the car agent and are used only for PHV and BEV vehicles, sized according to car specification (HEVs are assumed to be efficient ICE cars since they cannot be externally charged). Functionality includes charge state management, rapid charger search functions and handling of low charge events.

- Car Owners: selected from the UK National Travel Survey [223] and remaining constant throughout. Contains functionality related to drive cycle and initiates car journeys, maintains charging knowledge and individual budgets. Passes satisfaction and status information to car-owning peers and raw satisfaction data to linked consumat.

- *Consumats* : inextricably linked to car owners and act as the decision-making agent for the owner. The *Consumat* maintains a log of satisfaction and variance with peers and media received and carries out evaluation of car market when thresholds are exceeded.

- Households: car owner-matched dataset from UK National Travel Survey. Household agents collect home charging data and enable sharing of household income between car-owning members. Statistics on socioeconomic groups and home charging are aggregated at this level.

- Adverts: advert agents are created by a separate media agent and allow information about car models and government policy to be dispersed through the car owner agent set. Adverts are replaced on a regular basis.

In addition to these agents (where multiple copies of each exist), four other single agents are responsible for global functions including:

- Main:
    - model initialisation and statistics collection
    - global common functions such as depreciation
    - taxation and government policy
    - fuel price based on a looping historic data set plus taxes
- Manufacturer:
    - creation of new cars in car agent population
    - adjustment of car costs with reducing battery costs
    - calculation of generic Total Cost of Ownership (TCO)
- Media:
    - generation and deletion of advert agents
    - distribution of adverts to car owners/consumats
- Charging:
    - location of charging infrastructure
    - growth and kW ratings over time

Being a 'bottom-up' ABM, the key flows of information are from individual car and car owner agents, operating under various rules, up through household groupings and/or charging locations where statistical analysis and demand profiles are collated. Where top-down functionality, such as government policy that applies across a range of agents, is required this is implemented in the main agent and other single-agent classes such as the manufacturer and media agents.

3.2 Main agent

The main agent includes start-up actions, policy related data and a number of functions used by multiple agents. In this section, detailed functional descriptions are provided and the data sources used to parametrise the model are identified. Where start-up functions are included in the main agent, but relate to initiation of other agent classes, these are described within the relevant agent class.

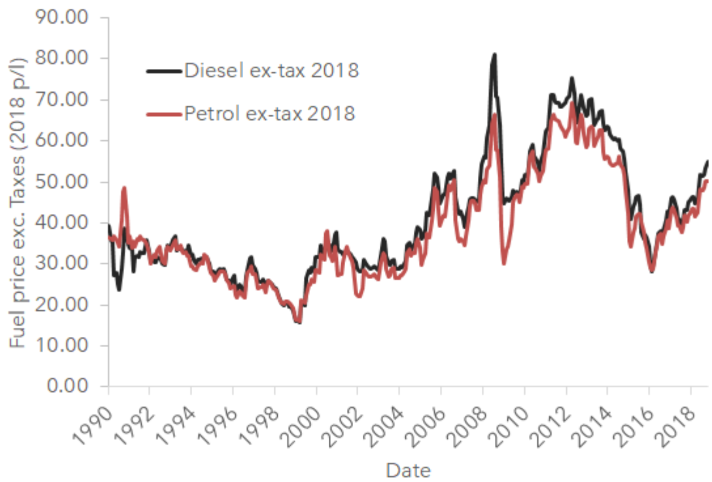


Figure 3.2: UK pump prices stripped of taxes and adjusted to 2018 GBP sourced from [220]

3.2.1 Fuel pricing

Petrol and diesel prices in the simulation are drawn from UK Government published monthly pricing data from January 1990 to October 2018 [220]. The prices were stripped of duty and Value Added Tax (VAT) and adjusted to 2018 GBP to reflect the un-inflated costs used elsewhere in the simulation; see Figure 3.2. This data is used as a raw refined fuel price which loops back to the start at the end of the dataset and to which is added the tax and duty applicable at the time. This strategy was adopted to provide real data in the hindcast period and a forecast price reflective of historic price volatility. The base assumption for projections is that VAT remains at 2020 levels and a fuel price escalator of 3% per annum is included on duty. The simulation ignores any elasticity in mileage with fuel price.

3.2.2 Electricity pricing

Electricity prices are fixed in the base model as shown in Table 3.1 and are reflective of typical consumer prices payable in the UK for different types of charging.

3.2.3 Emissions

Emissions from Petrol and Diesel cars are based on standard fossil/biofuel mixes at 2018 of 2203.07kgCO_2e l^{-1} and 2626.94kgCO_2e l^{-1} sourced from 2018 UK Government company reporting factors [221]. Note that the 'e' suffix indicates that all seven of the main greenhouse gases are included in the emissions figure adjusted (for their lifetime in the atmosphere) to a CO_2e (100 year lifetime).

Table 3.1: Electricity Tariffs

Tariff	Power kW	Timing	Cost p/kWh	Source
Uncontrolled (anytime)	7.2	Anytime	14.0	[32]
Controlled Charge (managed)	1.4-7.2	Anytime	7.0	[32]
Time-of-Use (ToU) (off-peak)	7.2	00:00-07:00	7.8	[32]
Rapid Charging (car limited)	50-150	Anytime	30.0	[241]

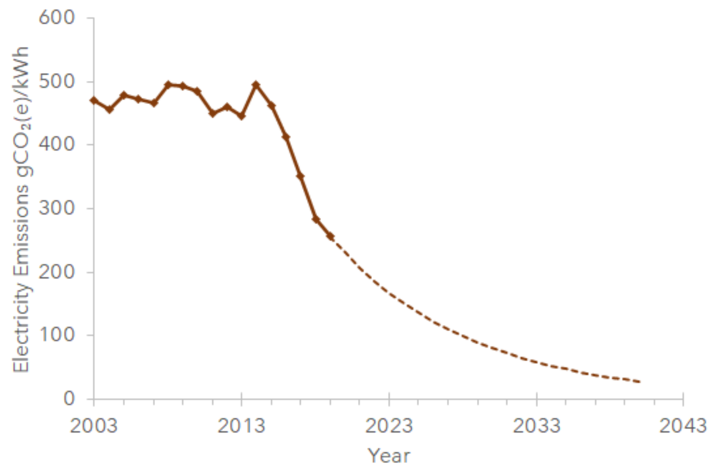


Figure 3.3: UK electricity supply emissions coefficient, actual and forecast from [221]

EV emissions are calculated based on a common emissions factor for all charging using historic annual grid emissions to 2019 [221] and reducing by 10% each year thereafter in line with UK Government projections. See Figure 3.3.

3.2.4 Non-fuel tax environment

From 2003 to 2020, the model replicates the UK tax environment across Vehicle Excise Duty (VED) and Benefit-in-Kind (BIK) contributions. BIK is an equivalent salary value used to determine the tax payable by company car owners. Both these taxes have had emissions related components over the duration of the hindcast simulation. The model includes provision to add future tax regimes, but in the base simulation, the regime at 2022 (the latest known at the time) remains in force until the end. The detailed rates used in the simulation are available from UK Government web resources [219]; only the key features are described here.

Vehicle excise duty

Up until 2010, a single UK Vehicle Excise Duty (VED) based on vehicle emissions was payable each year; increasing numbers of emissions bands were added, with just 4 in 2001 but 8 by 2009, ranging from zero for a car with under 100gCO_2 km^{-1} to £405/year for those with emissions over 255gCO_2 km^{-1}. From 2010 a 'Year 1' VED was introduced payable on first registration. Initially cars emitting less than 140gCO_2 km^{-1} paid nothing with those emitting over 255gCO_2 km^{-1} paying £1000; this high emissions category was increased to £2000 by 2017. Annual VED rates remained linked to emissions until 2016, when they ranged from zero to £515 per annum. For cars registered after 2016, those with emissions under 100gCO_2 km^{-1} continued with zero VED, all others were charged £140 per annum.

Benefit-in-kind

BIK rates have also been used to incentivise the procurement of lower emissions vehicles. The rates correspond to the percentage of the vehicle list price that is added to an employee's salary as a 'benefit-in-kind' for the purposes of calculating income tax and National Insurance (NI) contributions. NI is a form of tax which determines benefits and pensions and is payable by both individuals and businesses for their employees. Thus BIK rates affect both the take-home pay of employees with company cars and post-tax profits of businesses offering employee vehicles. BIK rates have been changed every year and there have been occasional anomalies, such as BEVs receiving a zero BIK rate from 2010 to 2017, but this being increase to 13% then 16% in 2018 and 2019 respectively with a planned reduction to 2% for 2020. In 2019 the government announced that zero emission cars would have a zero BIK rate in 2020, 1% in 2021 and 2% in 2022; the simulation has been run with a figure of 2% from 2020 onwards as per the original government announcement.

In a further change, PHVs, which were regarded as zero emission prior to 2018, were required to deliver a specific battery-only range to obtain BIK benefits; only one of the PHVs modelled was able to meet the first range band of 48km, which provided only a 2% point reduction in BIK rate.

A monthly update revises the BIK tax rate for each vehicle based on government policy extant at the time.

Table 3.2: Car Types and Models

Model	Segment	Accel. 0-60(s)	Battery kWh	EV Eff. km/kWh	ICE Eff. l/100km	Range km	Introduced Date	Price New GBP	Maint. GBP/yr	Tailpipe CO2 gCO2(e)/km	Aspiration Index	Example Car
BEV-A-15-02	Mini	15.4	15	10.00	0.00	145	01-01-20	20,500	60	0	0.120	Citroen C0
BEV-B-22-06	Supermini	11.4	22	6.31	0.00	139	01-01-13	25,000	63	0	0.390	Renault Zoe
BEV-B-52-48	Supermini	11.4	52	6.20	0.00	322	01-01-20	25,670	64	0	0.390	Renault Zoe ZE50 R110
BEV-C-24-10	Lower Medium	11.1	24	5.70	0.00	137	01-01-11	30,000	130	0	0.427	Nissan Leaf
BEV-C-28-44	Lower Medium	11.5	28	6.00	0.00	168	01-09-15	25,825	130	0	0.427	Nissan Leaf 30kWh
BEV-C-36-45	Lower Medium	7.9	36	6.00	0.00	216	01-02-18	29,790	130	0	0.427	Nissan Leaf 40kWh
BEV-C-56-46	Lower Medium	7.3	56	5.90	0.00	330	01-06-19	35,895	130	0	0.427	Nissan Leaf 62kWh
BEV-D-48-15	Upper Medium	5.6	48	6.57	0.00	312	01-07-19	40,500	50	0	0.342	Tesla Model 3 SR+
BEV-D-73-47	Upper Medium	4.6	73	6.30	0.00	457	01-07-19	47,990	120	0	0.342	Tesla model 3 LR
BEV-E-95-20	Executive	5.5	95	5.70	0.00	542	01-07-12	93,000	233	0	0.533	Tesla Model S
BEV-E-95-49	Executive	3.8	95	5.48	0.00	521	01-05-19	78,690	50	0	0.533	Tesla Model S
BEV-F-87-25	Luxury	5.7	87	4.25	0.00	368	01-12-19	68,000	170	0	0.933	Audi e-tron 55 Quattro
BEV-G-71-30	Sports	4.0	71	5.20	0.00	369	01-02-20	80,000	200	0	1.000	Porche Taycan
BEV-H-39-40	Dual Purpose	9.4	39	7.50	0.00	293	01-01-19	30,000	75	0	0.640	Hyundai Kona
BEV-H-64-41	Dual Purpose	7.4	64	7.50	0.00	480	01-01-19	35,495	89	0	0.640	Kia e-Niro
BEV-H-90-35	Dual Purpose	4.8	90	5.70	0.00	513	01-01-17	100,000	250	0	0.640	Tesla Model X
BEV-H-95-50	Dual Purpose	4.6	95	4.80	0.00	456	01-06-19	83,690	50	0	0.640	Tesla Model S
BEV-I-38-51	Multipurpose	14.0	38	4.88	0.00	185	01-06-18	29,255	130	0	0.319	Nissan EV200
BEV-I-64-52	Multipurpose	4.6	64	5.85	0.00	374	01-02-20	33,795	60	0	0.319	Kia Soul
DIE-B-00-04	Supermini	8.9	0	0.00	5.00	1200	01-01-03	18,000	180	107	0.390	Ford Fiesta
DIE-C-00-08	Lower Medium	8.3	0	0.00	4.15	1205	01-01-03	24,000	240	106	0.427	VW Golf 2.0 TDI
DIE-D-00-12	Upper Medium	8.4	0	0.00	4.34	1521	01-01-03	25,630	256	108	0.342	VW Passat
DIE-E-00-17	Executive	7.8	0	0.00	4.55	1099	01-01-03	39,000	390	117	0.533	Audi A6
DIE-F-00-22	Luxury	6.0	0	0.00	5.43	1436	01-01-03	70,000	700	143	0.933	BMW 7 Series
DIE-G-00-27	Sports	6.0	0	0.00	6.00	833	01-01-03	150,000	900	158	1.000	DNE
DIE-H-00-32	Dual Purpose	8.5	0	0.00	7.63	1009	01-01-03	48,000	480	197	0.640	Landrover/Rangerover
DIE-H-00-42	Dual Purpose	11.9	0	0.00	3.83	1567	01-01-06	22,630	226	99	0.640	Nissan Qashqai
DIE-I-00-37	Multipurpose	12.5	0	0.00	4.03	1365	01-01-03	23,930	239	105	0.319	Citroen Picasso
HEV-C-00-09	Lower Medium	10.3	0	0.00	3.43	1458	01-01-03	32,000	480	78	0.427	Toyota Prius
HEV-D-00-13	Upper Medium	8.2	0	0.00	4.10	1463	01-01-19	34,000	510	90	0.342	DNE
HEV-E-00-18	Executive	8.0	0	0.00	4.50	1111	01-01-19	45,000	675	99	0.533	DNE
HEV-F-00-23	Luxury	7.0	0	0.00	4.50	1111	01-01-20	50,000	750	99	0.933	DNE
HEV-G-00-28	Sports	6.0	0	0.00	6.00	833	01-01-20	150,000	900	132	1.000	DNE
HEV-H-00-33	Dual Purpose	9.0	0	0.00	6.00	833	01-01-19	50,000	750	132	0.640	DNE
HEV-I-00-38	Multipurpose	13.0	0	0.00	6.00	833	01-01-20	31,000	465	132	0.319	DNE
PET-A-00-01	Mini	12.2	0	0.00	4.10	1220	01-01-03	9,000	90	95	0.120	Citroen C1
PET-B-00-03	Supermini	9.7	0	0.00	6.10	984	01-01-03	16,000	160	111	0.390	Ford Fiesta
PET-C-00-07	Lower Medium	8.8	0	0.00	5.04	992	01-01-03	22,000	220	113	0.427	VW Golf 1.5 TSI EVO
PET-D-00-11	Upper Medium	8.1	0	0.00	5.33	1107	01-01-03	23,120	231	115	0.342	VW Passat
PET-E-00-16	Executive	7.5	0	0.00	6.72	744	01-01-03	40,000	400	153	0.533	Mercedes E Class
PET-F-00-21	Luxury	5.4	0	0.00	8.07	967	01-01-03	65,000	650	159	0.933	BMW 7 Series
PET-G-00-26	Sports	3.9	0	0.00	11.50	678	01-01-03	162,000	900	255	1.000	Aston Martin DB11
PET-H-00-31	Dual Purpose	7.0	0	0.00	9.74	924	01-01-03	47,000	470	222	0.640	Landrover
PET-H-00-43	Dual Purpose	10.9	0	0.00	5.60	1071	01-01-06	20,880	209	129	0.640	Nissan Qashqai
PET-I-00-36	Multipurpose	11.9	0	0.00	5.23	1052	01-01-03	23,760	238	119	0.319	Citroen Picasso
PHV-B-08-05	Supermini	6.6	8	5.70	5.50	589	01-01-19	32,000	480	55	0.390	Mini PHV
PHV-D-10-14	Upper Medium	7.2	10	5.05	5.50	959	01-06-14	37,000	555	40	0.342	VW Passat
PHV-E-10-19	Executive	8.2	10	4.50	6.00	878	01-01-20	48,000	720	66	0.533	DNE
PHV-F-09-24	Luxury	5.2	9	2.75	8.00	600	01-01-17	73,130	900	54	0.933	BMW 7 Series
PHV-G-12-29	Sports	4.5	12	4.00	10.00	466	01-01-15	127,000	900	46	1.000	BMW i8
PHV-H-12-34	Dual Purpose	10.6	12	3.70	7.00	687	01-10-17	37,000	555	41	0.640	Mitsubishi Outlander
PHV-I-09-39	Multipurpose	6.7	9	4.40	7.00	753	01-01-19	35,300	530	77	0.319	BMW 225xe

3.3 Car manufacturer agent

A single car maker agent contains the functionality to generate cars and sets the price and 'aspiration' level for each vehicle. Calculations for TCO are also calculated in this module.

3.3.1 Car types and models

The set of cars includes a range of models across all segments. AFVs are typically based on the parameters of a specific model sourced from [84]. Petrol and diesel only cars are included in the form of generic vehicles with data sourced from [176]. All the cars included in the simulation, with examples of typical cars, are given in Table 3.2 (DNE indicates no models existed at the time the data was generated.). The 'Price New' is the cost of the vehicle at the date of introduction with any Government incentives applied.

Each month the cost of a battery pack is updated using data from a battery price survey conducted by Bloomberg New Energy Finance [26], see figure 3.4. The cost of an EV is recalculated by deducting the battery cost in the year of introduction from the vehicle price to provide an estimate of the glider price (excluding battery). A revised pack cost from Figure 3.4 for the current month is added back to the glider price to determine the sale price of the newly made vehicle in that month. The pack cost was converted from USD to GBP at a fixed exchange rate of 1.4USD/GBP. Figure 3.4 also plots the forecast cost of a 40kWh BEV based on the cost of a 2010 24kWh Nissan Leaf using the technique described; the 'Actual 40kWh BEV' cost plotted is for a new model 40kWh Nissan Leaf first introduced in 2018 and shows a very good fit to the forecast cost. Bloomberg actually forecast that BEVs will reach price parity with ICE cars in 2025. Based on battery cost reduction alone, this is not the case as illustrated by the cost of 'C' segment petrol car in the figure. This is thought to to be due to cost reductions in the glider, resulting from mass production and design refinements such as using the battery pack assembly as a structural component. The effects of a 2% per annum reduction in glider cost from 2020 is also illustrated and shows that this delivers price parity in 2025.

A margin index, used to determine the amount of advertising of each model, is also recalculated monthly. The details of this calculation are contained in 3.4.

The model assumes that any car less than 6 months old is new for the purposes of a purchaser and each month cars are manufactured such that there is always availability. Cars are only manufactured if they are within the production start and end dates defined in the car data set; this enables the manufacture of ICE cars to be stopped according to government policy.

3.3.2 New car model creation

After 2020, the simulation enables the creation of new models of EV. A record in the car data database records the number of occasions when each model of pure EV has been rejected due to low range. When this number exceeds a defined percentage, set to 1%, of the number of car owners, that model will be upgraded at the next monthly update provided that it has not been introduced within the last 12 months. A BEV is upgraded by adding 50km of range. In order to estimate the new battery pack size, the Worldwide Harmonised Light Vehicle Test Procedure (WLTP) efficiency is adjusted down using a factor of -0.003 of the 50km range increment based on the analysis in Figure 3.5. Whilst the correlation here is poor, the objective is to provide some element of battery weight to range trade-off. Once a BEV has been been upgraded, it is tagged to avoid future upgrades, but remains

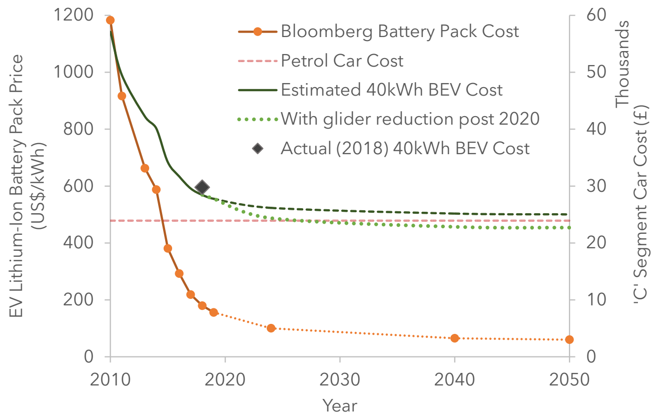


Figure 3.4: EV battery pack pricing based on Bloomberg survey data [26], extrapolated using forecast Bloomberg pricing with impact shown on estimated and actual 40kWh 'C' segment BEV.

on the market. The range-upgraded model is available to be upgraded further as required.

3.4 Media agent

A media agent determines which cars to feature in the media on a quarterly basis; the information is described here as adverts, but can be considered to include other features such as car reviews in magazine and on the web.

3.4.1 Model advertising probability

Adverts are created for each model with a probability in proportion to an indicative profit margin for that model. This margin is based on the cost of the vehicle and the proportion of that power train in the last year's sales. Accurate profit margins were not readily available; a range of sources were used in developing this estimate [7, 15, 137]

For vehicles of a power train which comprised 10% (F_t) or more of the previous year's sales, the base profit margin at time t is estimated using Equation 3.1, with $M_{b,t}$ constrained between the minimum and maximum margins, 8% and 20% respectively.

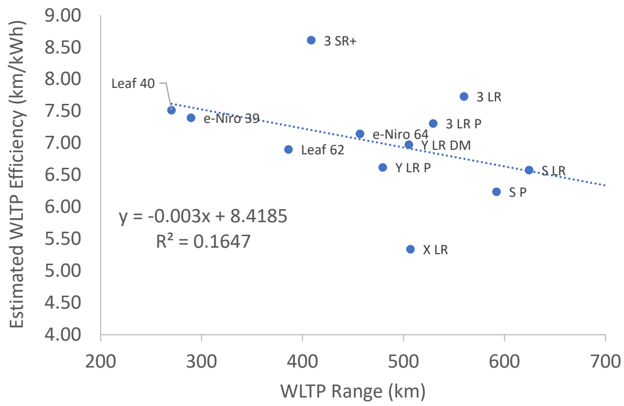


Figure 3.5: Estimated WLTP efficiency vs range for a selection of BEVs. Cars were chosen where manufacturer make a single model with different ranges. WLTP efficiency is calculated based on the estimated usable battery capacity from EV database [84] (Leaf - Nissan, e-Niro - Kia, all others are Tesla variants)

$$M_{b,t} = \frac{(P_t - P_l)}{(P_h - P_l)}(M_h - M_l) + M_l \tag{3.1}$$

where:	$M_{b,t}$	=	base profit margin at time t
	P_t	=	sales price of model at time t
	P_l	=	notional lower price limit (£5,000)
	P_h	=	notional upper price limit (£80,000)
	M_l	=	lower margin (8%)
	M_h	=	upper margin (20%)

Where a car has not reached F_t% of sales, the margin is assumed to be reduced due to poorer economies of scale and new technology costs [15] and the margin set according to Equation 3.2.

$$M_{n,t} = M_{b,t} \times \frac{F_{p,t}}{F_t} \tag{3.2}$$

where:	$M_{n,t}$	=	new power train model profit margin at time t
	$F_{p,t}$	=	power train sales fraction at time t
	F_t	=	threshold above which normal margins apply

The media function uses this margin as the probability that an advert for a particular model will be generated at any given time. However, in the first year after introduction of a new model, 0.05 is added to the probability of an advert being generated, meaning that new power trains are advertised, but not to the extent of ICE vehicles, until profitability increases to the same order.

A collection of 10 models to be advertised is generated each month, some of which may be duplicates (e.g. representing different manufacturers). No more than 100 adverts are live at any time, with the oldest adverts being removed each month. Thus, on average, an advert is live for 10 months.

3.4.2 Advert content

For each model to be advertised, an array of data corresponding to consumer satisfaction indices is generated. Values for energy costs are based on an annual distance of 15,000km, with tax and fuel costs based on the tax regime and fossil fuel prices extant at the time. The electricity cost is assumed to be the uncontrolled cost, i.e. a typical day-time tariff. Values in the data were adjusted with bias to represent more optimistic presentation of facts in advertising and more realistic information that may be presented in car reviews. The bias was applied by multiplying the actual value by $1 + \mathcal{N}\left(0, 0.08^2\right)$ to give a variation where 99% of values fall within +/-25% of the unbiased value. In some case, see Table 3.3 , this was limited to bias in one direction only. The application of this bias means that some drivers may receive positive information about a model whilst other may receive negative information, and a few will have conflicting information. Index values (reliability and aspiration) are limited between 0 and 1.

3.4.3 Advert delivery

Each day one advert from the collection is selected at random and sent to a randomly chosen 2% of car owners. Each car owner adds the advert to their media memory on a first-in-first-out basis. In the base model all agents have a memory for 10 items of media.

3.5 Charging agent

The charging agent updates the charging infrastructure on a quarterly basis across the two main types of public charging:

Table 3.3: Advert content and bias

Item	Base Value	Bias Low	Bias High
Reliability	1	✓	x
Range	(a)	✓	✓
Maintenance Cost	(a)	✓	✓
Tax Cost	(b)	✓	✓
Fuel Cost	(b)	✓	✓
Tailpipe CO_2e	(a)	✓	✓
Performance	(a)	✓	✓
Segment	(a)	x	x
Power Train	(a)	x	x
Aspiration	(a)	x	✓

Notes
(a) - data as per 3.3.1
(b) - data calculated from fuel costs/tax regime at time of advert generation

1. Major Route Charging; Direct Current (DC) rapid units designed primarily for en-route re-charging.
2. Destination Charging, subdivided into:
   - Shopping destinations;
   - Work-time charging; and
   - Social destinations.

In principle, the functions that describe infrastructure availability can be considered as driven by government policy in regard to timing, since private sector investors are unlikely to invest without either direct financial support (as has been the case in the UK) or indirect action such as the ban on the sale of ICE cars.

3.5.1 Major road routes: en-route charging

This functionality deals with en-route rapid DC charging provision. Rapid chargers are used by cars when the remaining range is less than 20km and they cannot reach the destination without re-charging. For planned journeys, i.e. those contained within the car owner's weekly National Travel Survey [223] (NTS) schedule, the probability of a charger being available is 1, on the basis that regular journeys would generally be completed without charging issues. For unplanned journeys, the model selects a distance to the next rapid charger from a uniform distribution between zero and the major roads fast charger separation at the time of the journey. If the car does not have sufficient range then a 'Low SoC' event is triggered resulting in a 'breakdown' and decrease in range satisfaction. The target charger separation is 20km meaning that, referring to Figure 3.6, by 2040 all journeys can be undertaken without running out of charge.

Equation 3.3 was used to determine the mean separation between chargers using data on number of locations and chargers sourced from ZapMap [241] and illustrated in Figure 3.6. This approach is somewhat imprecise since the totals include Tesla Supercharger locations which can only be used by Tesla cars, and also a mix of Chademo and CCS (Combined Charging System) connectors. Although CCS is now the UK standard, Chademo was used by Nissan on the Leaf until 2018, which was by far the most popular EV in the UK. Tesla locations also tend to have many connectors, as many as 16 in some cases. Whereas, Ecotricity, the other early UK network, might typically have one or two chargers each with two different types of connector (Chademo and CCS), only one of which would be suitable for any individual's car. To take account of the high number of Tesla chargers per location, the starting point was assumed to be 4 across all networks in 2011 and increasing at a rate of 1% per quarter.

$$S_{r,t} = \begin{cases} \frac{N_{r,t} \times S_p}{f(t)} & t < 2019 \\ max[S_m, G_r S_{r,t-1}] & t \geq 2019 \end{cases} \tag{3.3}$$

where:	$S_{r,t}$	=	mean major route rapid charger separation at time t
	$N_{r,t}$	=	number of chargers per location at time t
			assuming a quarterly growth rate of 1%
	S_p	=	total length of primary routes (50,240km [65])
	$f(t)$	=	estimated charger separation from Figure 3.6
	S_m	=	target separation of chargers (20km)

When a car reaches a rapid charger, a queuing delay is implemented with a probability as defined by Equation 3.4. Thus a car arriving at a rapid charger at any hour where historical charge point demand is less than the average will not experience any delay, but above this there is an increasing probability of having to wait, defined by an over-capacity factor, k. At $k = 10$, used in the model, the peak time wait probability is 0.35. The actual wait time is hypothesised as having a mean of 15 minutes and standard deviation of 5 minutes.

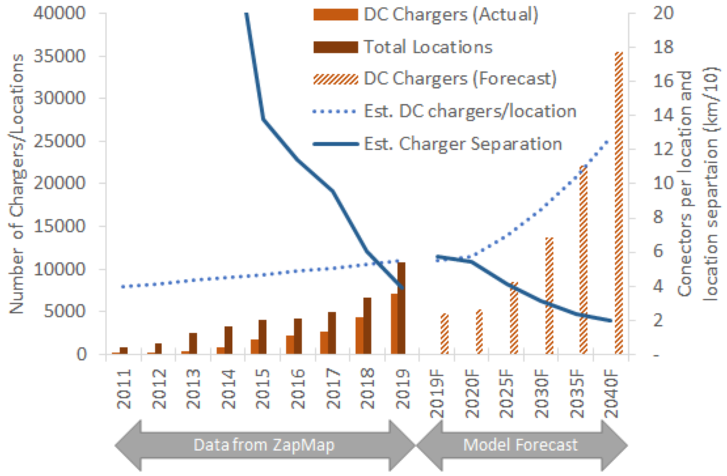


Figure 3.6: Deployment of rapid DC chargers from [241]. DC chargers can be broken into Chademo (initially 100% falling to c43%), CCS (rising to ca. 47%) and Tesla (rising to ca. 10%). Forecast is intended to reflect chance of charger being suitable for car.

$$Q_t = k(\bar{x} - x_h) \tag{3.4}$$

where: Q_t = probability of having to wait for a charge at time t
k = factor representing installed overcapacity ($k = 10$)
$\bar{x}$ = all-time mean hourly fast-charge probability
x_h = all-time probability of charging at hour h in day

Having arrived at the charger, the mean charge rate (and therefore time to charge) is determined from a PERT distribution, to reflect grid constraints and thermal limits, with a maximum set to the maximum car charge rate. The minimum and mode start at 22kW and 40kW respectively and increase by 1% each quarter, reflecting the increasing charging speeds available in the market. This rate results in a minimum and mode of 70kW and 126kW respectively by 2040. Range satisfaction is adjusted at the end of each rapid charge event according to Equation 3.5. A survey for Transport Focus [213] indicates current (ICE dominated) motorway service area dwell time of 20 minutes, so this calculation aims to penalise charging durations of longer than 20 minutes.

$$S_{r,t} = S_{r,t-d} - 0.1 S_{r,b} \frac{d - 20}{10} \tag{3.5}$$

where: $S_{r,t}$ = Range satisfaction at time t

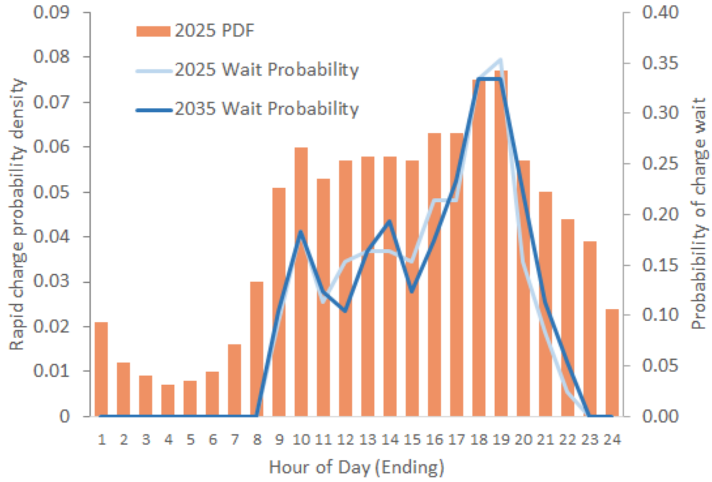


Figure 3.7: Example probability density function of rapid charging times (2025 deployment levels); the probability of having to wait for a charge is a function of this PDF as defined in Equation 3.4, where $\bar{x}$ is the mean value of the PDF.

$S_{r,t-d}$	=	Range satisfaction immediately prior to stop
$S_{r,b}$	=	base range satisfaction decrement (0.1, all owners)
d	=	total duration of charging stop in minutes

3.5.2 Destination charging

Destination charging is generally considered to be charging at locations where other activities are carried out. In this simulation, workplaces (more accurately the opportunity to charge whilst at work), social destinations such as sport facilities, entertainment venues, restaurants and shopping destinations (town centres and other locations) are included. Whilst most destination charging is slower AC charging (typically 32A/7.4kW), this is not exclusively the case and some supermarkets in particular have been installing DC rapid chargers (e.g. Morrisons [152]), which are more suited to the average duration of a food shopping trip.

Figure 3.8, sourced from ZapMap data [241], shows that AC charging provision, which is exclusively destination charging, has been growing exponentially since 2011. Various charging providers have agreements in place to install chargers at hotels, shopping and leisure facilities, see for example [182], and this rate of growth is expected to continue for sometime, supported, in some cases, by the UK government's charger grant programme [172]. Based on Figure 3.8, the availability of charging at each of these locations is hypothesised as an asymmetrical sigmoid

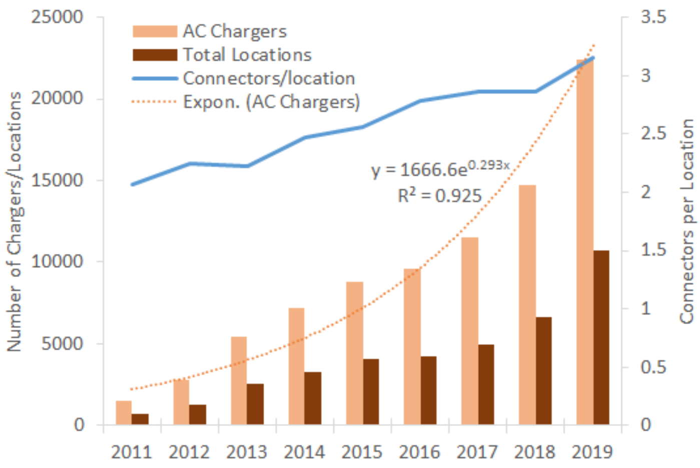


Figure 3.8: Deployment of AC destination chargers from [241], illustrating exponential growth.

function describing the probability over time as illustrated in Figure 3.9. From ZapMap data, the percentage of rapid chargers in the total installed base varied from 16-23%; the model assumes a probability of 0.2 that any destination charger is a rapid charger.

Location charging probability matrix

The probabilities of charger availability by location are compiled into a single matrix each quarter. Table 3.4 is an example of the matrix in 2018. Car owners use this matrix to determine the probability of being aware of charging provision at locations they visit, thus increasing their 'Charging Knowledge'. Refer to Section 3.7.2.

3.6 Household agents

This subsection describes functionality associated with households.

Household selection, classification and location

The NTS 2016 data set includes some 7,328 households. The model environment is unable to process this number of agents when combined with the required number of car agents, thus a random subset of households were chosen. The subset also excludes households without a car; although such households may acquire a car in future, the number of car owning households has remained flat over the last

Table 3.4: Charging probability matrix - example in 2018

NTS Location	Uncontrolled	ToU	Controlled	V2G	Rapid
Work	0.015	0.000	0.000	0.000	0.000
InCourseOfWork	0.007	0.000	0.000	0.000	0.003
EducationDest	0.007	0.000	0.000	0.000	0.003
FoodShopping	0.036	0.000	0.000	0.000	0.007
NonFoodShopping	0.036	0.000	0.000	0.000	0.007
PersonalMedical	0.007	0.000	0.000	0.000	0.003
PersonalEatDrink	0.009	0.000	0.000	0.000	0.002
PersonalOther	0.000	0.000	0.000	0.000	0.000
FriendsEatDrink	0.009	0.000	0.000	0.000	0.002
FriendsVisit	0.000	0.000	0.000	0.000	0.000
SocialOther	0.009	0.000	0.000	0.000	0.002
EntertainmentPublic	0.009	0.000	0.000	0.000	0.002
SportParticipate	0.009	0.000	0.000	0.000	0.002
HolidayBase	0.000	0.000	0.000	0.000	0.000
DayTrip	0.000	0.000	0.000	0.000	0.000
OtherNonEscort	0.000	0.000	0.000	0.000	0.000
EscortHome	0.000	0.000	0.000	0.000	0.000
EscortWork	0.007	0.000	0.000	0.000	0.003
EscortInWork	0.007	0.000	0.000	0.000	0.003
EscortEducation	0.007	0.000	0.000	0.000	0.003
EscortShopping	0.036	0.000	0.000	0.000	0.007
EscortOther	0.000	0.000	0.000	0.000	0.000
Home	0.000	0.000	0.000	0.000	0.000
Mid Journey	0.000	0.000	0.000	0.000	0.000

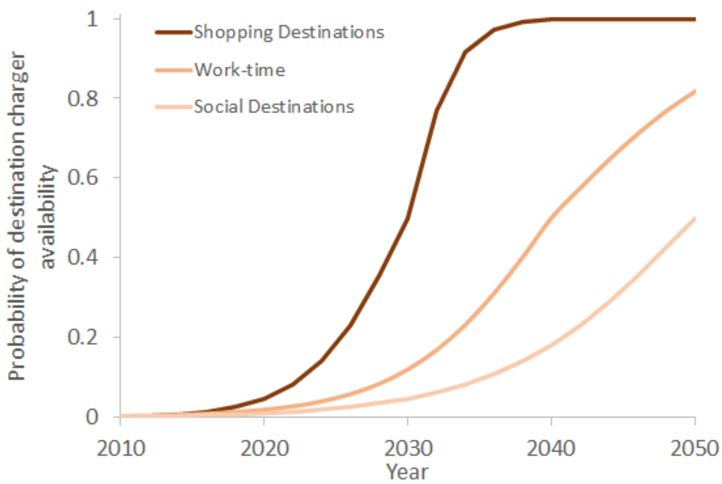


Figure 3.9: Hypothesised growth in destination charging availability expressed as the probability of charging being available at a give destination category and time

Table 3.5: ONS Supergroups, population fractions and sample correction

Ref	Supergroup description	2016 NTS data % total	2016 NTS data % total no car	2016 NTS data % group with car	Model sample % sample	Car owner correction	Household correction
1	*Rural Residents*	10.08	0.72	12.06	13.71	0.88	0.74
2	*Cosmopolitans*	3.21	1.51	2.18	2.10	1.04	1.53
3	*Ethnicity Central*	6.06	3.25	3.62	4.50	0.80	1.35
4	*Multicultural Mets*	13.80	3.83	12.84	13.61	0.94	1.01
5	*Urbanites*	20.21	3.08	22.07	21.92	1.01	0.92
6	*Suburbanites*	22.73	2.07	26.63	24.42	1.09	0.93
7	*Constrained City*	7.16	3.13	5.21	5.51	0.95	1.30
8	*Hard Pressed*	16.74	4.80	15.39	14.21	1.08	1.18
	Total without car		22.41				

15 years, see Figure 3.10, including only current car-owning households appears a reasonable simplification of the model.

The NTS data set does not provide detailed location data for households, but does provide data that can be mapped to UK Office for National Statistics (ONS) 2011 census area classifications (super groups) to provide information on the location and type of households to which vehicle owners belong. Table 3.5 sets out the ONS super groups and the proportions of households and car-owning households in each group. In the analysis, corrections are made to adjust the model output to match the car-owner fraction of the population when considering adoption rates of EVs, but where grid impacts are considered, a correction is made to represent the entire population, such that demand diversity takes into account non-car owning households. The ONS [229] also ascribe a super group to every postcode in the UK; the average number of households per postcode is 15.5 and, on average, they each cover an area of $0.14km^2$. To provide locational (and thus proximity) information for households, in this analysis the following subset of local authorities

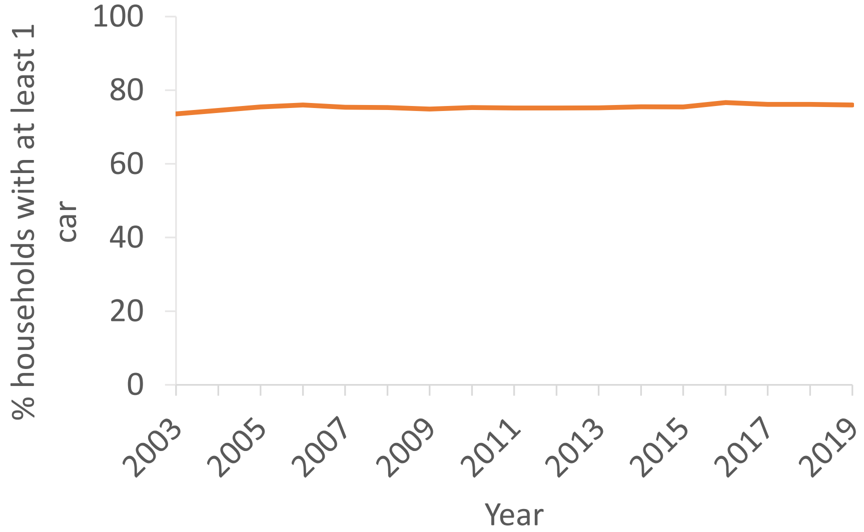


Figure 3.10: Households owning one or more cars from [223]

and their related postcodes have been selected:

- E08000019 - Sheffield City Council
- E08000016 - Barnsley
- E08000018 - Rotherham
- E07000037 - High Peak
- E08000034 - Kirklees
- E07000038 - North East Derbyshire
- E07000035 - Derbyshire Dales

These areas were included to ensure that there was a suitable mix of each supergroup, covering rural, suburban and city environments. Each household is randomly assigned a postcode which corresponds to the its ONS SuperGroup (Table 3.5) and the latitude and longitude of the centre point of the postcode provides a GIS location for the household. This allows meaningful spacial plots of car-type ownership and associated electricity demands (aggregated from car owner to

Table 3.6: Household Parking Access (source: [150])

Parking Type	UK Households %
On plot	60.39
Off-plot designated	6.13
Communal	7.44
None designated	26.04

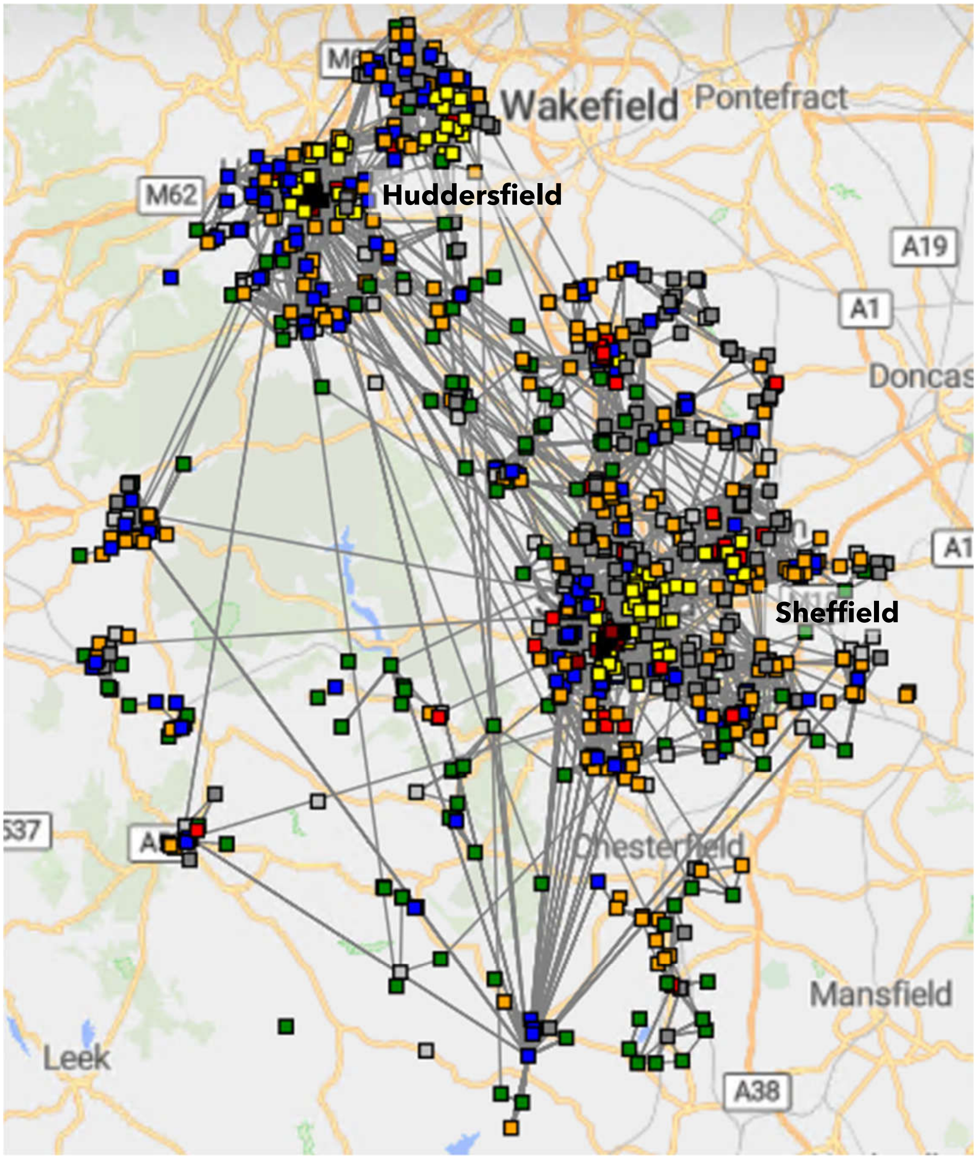
household and then to spacial area or social group) to be obtained. Figure 3.11 plots the social classification for all 1000 households in the base model over the included geographic area.

Household home charging

The English Housing Survey (EHS) [150] contains data on households that are most likely to have access to on-plot parking and therefore off-street charging. Table 3.6 summarises the data. This shows that about 60% of households could theoretically have access to home charging, whilst further 13.5% may be able to access local shared or dedicated facilities.

The EHS gives a breakdown of these data by broad housing type and these can, to a large degree, be mapped to NTS information on housing. Table 3.7 illustrates the mapping from EHS household type to NTS social class as used in the simulation. The NTS data does not discriminate between terraces and end terraces or bungalows and multi-storey detached and semi-detached houses; these were allocated in the percentages shown in the 'NTS Alloc' column. This approach resulted in a total of 67.7% of households having access to home (or dedicated) charging provision. This was regarded as consistent with the EHS total in Table 3.6 in that it suggests all households with on-plot parking and about 50% of those with off-plot or communal parking could regularly access charging whilst at home.

Households are assigned home charging capability based on the probability in Table 3.7 at the start of the simulation are assumed to adopt home charging on purchasing an EV.



ONS Code	ONS Description	Colour
1	Rural Residents	Green
2	Cosmopolitans	Dark Red
3	Ethnicity Central	Black
4	Multicultural Mets	Yellow
5	Urbanites	Blue
6	Suburbanites	Orange
7	Constrained City	Red
8	Hard-pressed Living	Grey

Figure 3.11: Plot of 1000 households simulated in base model showing spacial distribution, ONS classification and homophily-derived connections between peers.

Table 3.7: Household Home Charge Probability (based on [150] & [223])

			Rural Residents	*Cosmopolitans*	*Ethnicity Central*	*Multicultural Mets*	*Urbanites*	*Suburbanites*	*Constrained City*	*Hard Pressed*
Households in NTS		(%)	12.6	1.0	3.1	12.4	22.2	27.8	5.0	15.0
EHS House Type	EHS On-Plot	NTS Alloc								
End terrace	51.2	10	1.4	4.1	2.9	4.3	3.0	0.6	4.1	3.6
Mid terrace	31.6	90	12.6	37.3	26.1	38.8	27.3	5.4	37.2	32.5
Semi-detached	81.6	85	20.0	2.7	11.5	30.7	28.3	35.7	18.3	43.5
Detached	96.1	85	51.7	5.4	1.7	6.2	20.5	43.3	4.9	7.7
Bungalow	77.4		12.6	1.4	2.3	6.5	8.6	13.9	4.1	9.0
Converted flat	28.5		0.7	13.8	9.5	2.7	2.3	0.7	4.1	0.1
Purpose-built flat	26.2		1.0	35.1	45.9	10.8	9.8	0.4	27.3	3.6
Probability of home charging		Weighted Mean 0.68	0.81	0.36	0.37	0.54	0.63	0.84	0.45	0.63

3.7 Car owner agents

This section describes the functionality of the car owner agent and associated processes.

3.7.1 Income and budget

The income of each individual is set by reference to the NTS annual salary band (£0-£25k, £25-£50k, £50k+) and a set of look up tables corresponding to each band as illustrated in Figure 3.12. The salary data was sourced from the UK ONS (2018 data). Note that all costs in the model are referenced to 2018/2019 UK financial year; there is no inflation in the model. A household income was determined by summing the relevant individuals' incomes.

Each car owner is assigned a monthly car budget based on the household income and their share of household annual travel distance as per Equation 3.6. This strategy is used to ensure that in households with two or more cars where one or more individual is not earning, those individuals still have an adequate budget to run a car.

$$C_{i,j} = kI_j f(I_j) \times \frac{S_{i,j}}{S_j} \tag{3.6}$$

where:

where:	$C_{i,j}$	=	monthly car budget for car owner i in household j
	k	=	constant to adjust budget to UK average
	I_j	=	monthly household income of household j
	$f(I_j)$	=	fraction of household income - see Figure 3.13
	$S_{i,j}$	=	annual km travelled by owner i in household j
	S_j	=	annual km travelled by all car owners in household j

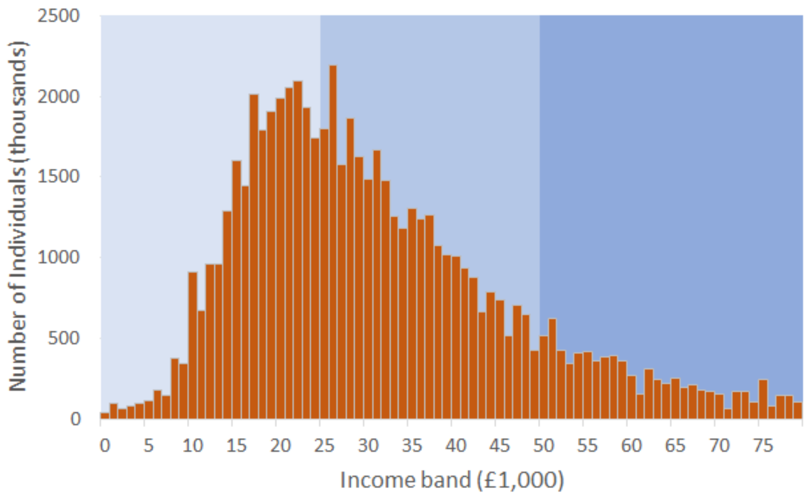


Figure 3.12: UK household income in £1000 bands. Data sourced from [229] with £25k bands available in NTS data shown in blue

Each car owner has an individual savings account from which car costs (purchase/lease, fuel/electricity, tax and maintenance) are deducted each month. The account was initiated with a balance set as a multiple of their monthly budget. The multiple was taken from a PERT distribution with a mode of 6, minimum of 0 and maximum of 12 (months). Whilst there is data available on average savings of UK individuals [87], there is little information relevant to the proportion assigned to new vehicle purchase or unexpected motoring expenses. Reviewing various new and used car finance offers on the web indicated deposits of around 10% are the norm. The average purchase price of a car in the UK was around £13,000 in 2019 [11], with the average price of a new car substantially more at £33,559 [37]. The average monthly budget was £320.00, so the mode of 6 times monthly budget gives ca. 5% of the average new car cost or ca. 15% of the purchase price of an average used car. These figures are considered to be consistent with the savings needed to buy the range of cars available.

If a car owner's savings balance exceeds 110% of their initial balance and the rate of change of savings is positive, then the car owner reduces their savings contribution by 5% per month down to a minimum of 80% of their starting monthly budget. The converse was applied to those with a balance below 90% of their starting balance.

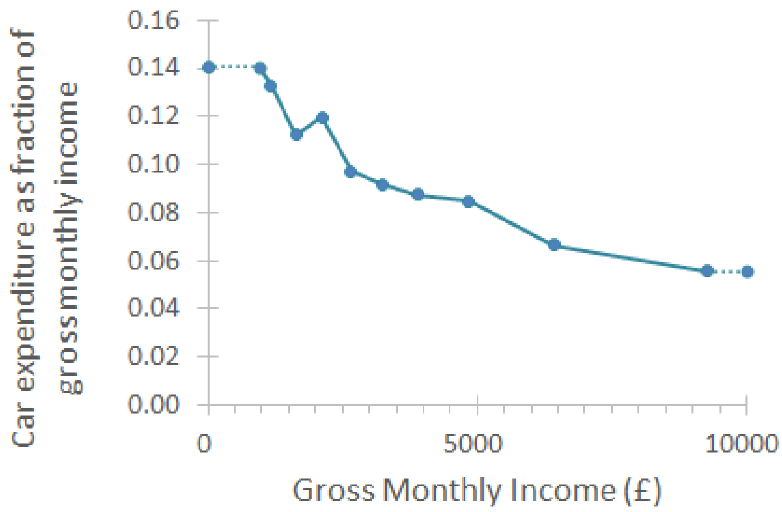


Figure 3.13: Car expenditure as a fraction of household gross monthly income. Data sourced from [228] with those items not included in the simulation (e.g. insurance) excluded.

Provided that the car owner is not leasing, then a savings balance less than 50% of the initial balance combined with a negative rate of change of savings, will result in immediate disposal of the car and the owner's satisfaction index being reduced to zero. A car owner without a car increases their monthly budget at 5% per month for each month that no suitable car can be found up to a maximum of 25% above their initial monthly budget.

3.7.2 Range knowledge

Each car owner has an index ranging from zero to one defining their knowledge of charging infrastructure, which is updated monthly based on a car-owner specific matrix of NTS destinations and charging types as defined in Section 3.5. That is, for each destination in the list of NTS possible destinations, together with an additional category of 'Mid Journey', each owner can have one or more of the following charging types available:

- Uncontrolled 7.2kW, charges car immediately on arrival
- ToU 7.2kW, charges car during off-peak (overnight) period
- Controlled 7.2kW max, uses demand control algorithm
- V2G Full V2G charger
- Rapid DC Rapid charging

Each month, the car owner's personal matrix is updated by sampling a uniform probability (between 0 and 1) and testing against the value in the charging agent matrix (see example Table 3.4). Once a car owner matrix element has changed from 0 to 1 that location and charging type is immutable. For each location with a charger, the car owner's charging knowledge index is incremented by 0.05. Further, the charging index is increased by 0.5 x ratio of peers with home chargers (indicating either the immediate peer or one of their household owns a chargeable car) to total peer group size, reflecting exchange of knowledge with BEV owning peers. The charging knowledge index is used to set the car owners range requirement.

3.7.3 Car range requirement

Prior to a car purchase, each driver re-evaluates their range requirement to generate a minimum range, below which a car will not be considered, and a target range. The range satisfaction for each car tested in the decision process is ranked between 0 and 1 from the minimum range to the target range.

Range-rhetorical drivers Drivers that fall into the 'die hard' or 'complacent' categories (see 3.7.4) were deemed to be 'range-rhetorical', i.e. range is used as an excuse for failure to purchase an EV without giving further thought to realistic requirements [165]. These drivers are assigned a minimum range of 600km and target range of 1000km, corresponding to typical ICE vehicle ranges. They only start to consider alternative range vehicles when either 60% of their peers are driving BEVs or when the longest range car available in the market (deemed to be any car in the car pool less than one year older than their previous car) has a range of under 1000km.

Other drivers For non-range-rhetorical drivers, the target range is set according to Equation 3.7. The objective of this function is to enable the car owner to drive their preferred non-stop distance without charging, but where charging knowledge is incomplete, this is increased to a maximum of twice their desired distance. Further, should EV's remain range restricted compared to ICE vehicles, the car owner reduces their desired range according to what is available in the market.

$$R_t = min[(S_n(2 - K_t) + S_c, R_{l,t}] \tag{3.7}$$

where: R_t = target range (km)
S_n = non-stop driving distance (see below)

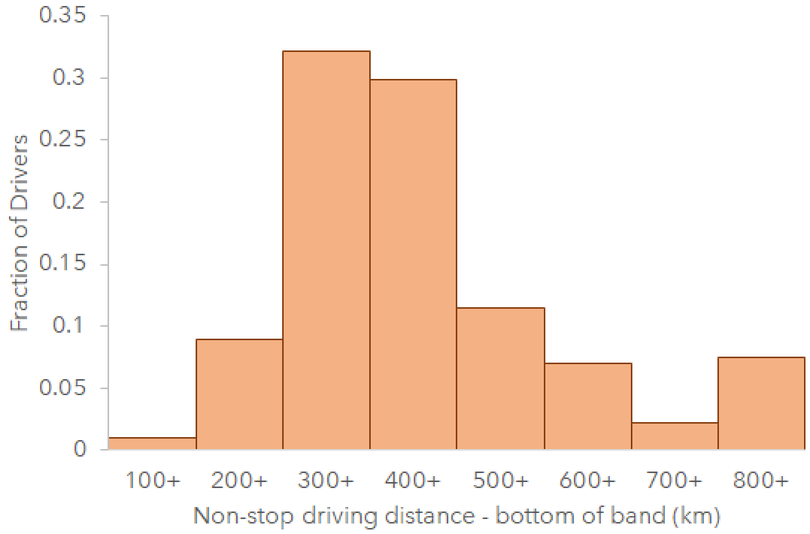


Figure 3.14: Non-stop driving distances on major routes assuming average 100km/h based on Royal Automobile Club (RAC) survey data [183]

K_t	=	charging knowledge at time t
S_c	=	comfort margin (see below)
$R_{l,t}$	=	longest range car < 1 year older than current

Non-stop driving range The desired non-stop driving range for a driver was determined from an RAC survey [183] which gives the maximum driving times for a sample of 1,010 drivers. UK Department for Transport statistics [66] indicate free-flow average car speed of 68mph (109km h^{-1}) on motorways and 50mph (80km h^{-1}) on single carriageway national speed limit roads. Thus the times were converted to a distance assuming a speed of 100km h^{-1} on the basis that these were typically primary route drives; see Figure 3.14

Comfort margin Each driver is further assigned a range comfort margin based on the work of Franke et al [93]. This indicates a psychological comfort margin in the range 5 to 200km, with a mean of 19.2km and standard deviation of 15.3km.

Minimum range requirement for non-range-rhetorical owners Non-range-rhetorical drivers adjust their minimum range requirement prior to each purchase decision based primarily on whether, within their household, they have access to a car with their desired target range. Where no other car is available, the minimum range is set to 10% below the target range, if an alternative car is available, the minimum range is set according to equations 3.8, 3.9 & 3.10, where:

R_m	=	minimum range (km)
S_{wm}	=	longest weekly trip in the driver's NTS record
S_w	=	weekly travel distance (NTS records)
R_c	=	comfort margin
K_t	=	charging knowledge at time t
$R_{l,t}$	=	longest range car < 1 year older than current

Owner has home charging

$$R_m = min[2S_{wm} + R_c, R_{l,t}] \tag{3.8}$$

Owner has only work charging

$$R_m = min[4S_{wm} + R_c, R_{l,t}] \tag{3.9}$$

Owner has access only to public chargers

$$R_m = \begin{cases} R_{l,t} & K_t = 0 \\ min\left[\frac{S_w}{K_t} + R_c, R_{l,t}\right] & K_t > 0 \end{cases} \tag{3.10}$$

In all the above cases, R_m is always reduced to 90% of R_t if $R_m > R_t$.

3.7.4 Car owner homophily and agent connection process

All household members are connected and thereafter additional connections are made based on an homophily index, designed to indicate similarity between car owning agents.

The NTS dataset provides banded data for individual's income (3 bands), education (degree or lesser only - 2 bands), social class (7 bands) and age (15 bands). Where there is no response in the survey, individuals are randomly assigned a band, except in the case of education, where an additional mid band is assigned to avoid all owners having the same education similarity index. Additional parameters for 'greeness', children and gender are also included in the homophily index. The greeness parameter is determined based on the work of J.Anable [6].

Table 3.8: Driver types (after [6]) and greeness

Driver Type	Proportion of Drivers %	Lowest Greeness	HighestGreeness
DieHard	20.43	0.00	0.20
Complacent	27.96	0.20	0.48
Malcontent	32.26	0.48	0.80
Aspiring Environmentalist	19.35	0.80	1.00

Drivers are randomly assigned to a type according to the probabilities in Table 3.8. Each driver is then assigned a greeness index based on a uniform distribution between the lower and upper thresholds shown in Table 3.8, corresponding to percentage range of driver types. A further function scales the greeness of each driver to limit it to a maximum value set for all drivers. This is designed to enable car-owner greeness to be increased through media and inter-peer communication over time. For the purposes of assigning a band for the homophily calculation, the index is converted to a number between 0 and 5. The physical proximity of driver agents is included in the homophily index, with those agents within 3km of each other being assigned a similarity of 1 and from 3 to 6km, a similarity of 0.5.

Each driver is also assigned a 'performance' weighting indicating the importance of car performance to them, for which acceleration is used as a proxy. This is determined using an inverse correlation to greeness with a coefficient of 0.5, though this is not used in the homophily index.

The homophily index is then calculated by comparing each agent in turn with every other agent. If an agent has the same index value then the correlation is defined as 1 if it is one either side of the other person then the correlation is defined as 0.5; any further separation results in a correlation of 0. A weighted average of these correlations, where all weights are set to unity, is then calculated to give a homophily score between agents between 0 and 1. Each agent is assigned a threshold for homophily above which they will connect with another agent. The threshold is set using a beta distribution with p=20, q=5 and constrained between 0 and 1. This ensures a range of connectivity in the model, with some car owners having no connections with whom they exchange car information and some having up to 50, with a mean of 9.1. The connectivity of agents in the model is illustrated in Figure 3.11. The Grannis Factor [102] for the network is 1.2, indicating a highly connected network rather than one comprised of non-interacting groups. However, it should be noted that peers only communicate information about their own car experiences; they do not pass on information about their peers' experiences.

3.7.5 Satisfaction measures

The car owner agent collates the satisfaction indices for each agent and these are passed to the linked *Consumat* agent at each vehicle evaluation event. The indices are as follows:

- Aspiration
- Reliability
- Range
- Maintenance cost
- Tax cost
- Energy cost
- Total cost
- Emissions
- Performance
- Segment
- Power train
- Purchase type

Separate indices are included for different cost components because it has been suggested that consumers' responses vary according to the manner in which costs are incurred. Allcott and Wozny [4], for example, suggest that consumers value discounted future fuel costs at 76% of the value they place on purchase costs. Grigolon, Reynaert and Verboven [104] discuss this issue in relation to tax policy and conclude that consumer heterogeneity, particularly in respect of annual mileage, plays a factor in how consumers value up-front vs ongoing costs. These conclusions are supported in the field of EV adoption by Bjerken et al. [25] in their review of incentives in Norway. Anecdotally, there is also evidence that consumers refer to cost components separately - such as not paying tax for EVs or their low maintenance costs compared to ICE vehicles.

Each of the satisfaction measures and their derivation are outlined here, with reference to other sections where calculations are performed in other agents, such as the car agent.

Aspiration

The aspiration value of a car is based on car type, value and age. Details of this are included in Section 3.9.6. The satisfaction measure is passed to the *Consumat* unchanged.

Reliability

Satisfaction in regard to reliability is updated each time a breakdown occurs and at the end of each incident free month according to equation 3.11.

$$S_{2,t} = \begin{cases} S_{2,t-1} - B_e - B_0 \times \frac{B_d}{B_{d_0}}, & \text{on breakdown event} \\ S_{2,t-1} + B_m, & \text{at end of zero breakdown month} \end{cases} \tag{3.11}$$

where:

$S_{2,t}$	=	vehicle reliability satisfaction index at month t
B_e	=	decrement in relibility index per event, set to 0.1
B_0	=	base reduction in satisfaction per B_{d_0}, set to 0.05
B_d	=	duration of current breakdown
B_{d_0}	=	base duration of breakdown, set to 1 day
B_m	=	increment in breakdown-free month, set to 0.066

Historically the duration of vehicle ownership has been increasing [135], this may be a function of increased reliability in vehicles, which may be accelerated with the adoption of EVs with their fewer moving parts. Thus this component of the satisfaction index enables exploration of vehicle reliability on turnover rate and is considered important in existence needs satisfaction.

Range

Satisfaction is decremented by the owner's defined satisfaction decrement, set to 0.1 in all analyses here, in the following circumstances:

- when an unplanned trip cannot be completed within 80% of the available range,
- each time the battery SoC falls below the anxiety threshold for the owner,

- if the battery SoC falls to zero whilst driving, a random delay is incurred and satisfaction is decremented by 3 times the owner's satisfaction decrement, and
- for the second and each subsequent fast charge during a single trip.

If none of the above events have occurred during a month, then the range satisfaction index is incremented by 0.025. The index value (0-1) is passed to the consumat.

Tax cost

The car owners annual tax cost is passed directly to the *Consumat* process.

Energy cost

The energy cost is passed to the car owner agent from the car agent each month and is the total cost of fuel and electricity (less any payments for V2G services) per km travelled. This figure is passed to the *Consumat* unchanged.

Maintenance cost

The maintenance cost is calculated in the car agent as described in Section 3.9.4. The annual rolling total cost is passed to the car owner agent each month and thence onto the *Consumat* unchanged.

Total cost

The total cost comprises an exponentially weighted moving average of the monthly tax, energy and maintenance costs, collected from the car agent, to which is added any monthly finance payments. This cost is passed unmodified to the *Consumat* agent.

Emissions satisfaction

Emissions satisfaction is calculated as an index between 0 and 1 where 0 represents zero emissions, 1 represents the emissions of the worst car in the fleet and 0.5 represents the average fleet emissions. Emissions are calculated on a per km basis each month according to Equations 3.12 and 3.13

$$E_t = \frac{Q_{e,t}F_e + Q_{p,t}F_p + Q_{d,t}Q_{d,t}}{100.d_t} \tag{3.12}$$

where:

E_t	=	emissions factor in month t, gCO_2e $100km^{-1}$
$Q_{e,t}$	=	electrical energy consumed in month
F_e	=	emissions factor of electricity consumed
$Q_{p,t}$	=	petrol fuel consumed in month
F_p	=	emissions factor of petrol
$Q_{d,t}$	=	diesel fuel consumed in month
F_d	=	emissions factor of diesel
d_t	=	distance travelled in month

Individual user satisfaction is given by:

$$S_5 = \begin{cases} \frac{1}{2} \cdot \frac{E_t}{E_{t,\mu}}, & E_t \leq E_{t,\mu} \\ \frac{1}{2}\left(1 + \frac{E_t - E_{t,\mu}}{E_{t,\max} - E_{t,\mu}}\right), & E_t > E_{t,\mu} \end{cases} \tag{3.13}$$

where:

$E_{t,\mu}$	=	average emissions factor in month t for all vehicles, gCO_2e $100km^{-1}$
$E_{t,\max}$	=	maximum emissions factor in month t for all vehicles, gCO_2e $100km^{-1}$

Performance

Performance is passed directly to the car owner and thence the *Consumat* based on the 0-100kph acceleration time of the vehicle.

Segment

Segment is passed directly from the car agent through the car owner to the consumat.

Powertrain

Powertrain is passed directly from the car agent through the car owner to the *Consumat* and uses the same algorithm as segment for the social need.

Purchase type

Purchase type comprises four options; direct purchase, personal loan, personal lease and company lease (which cannot be changed by the owner). These are compared as a modal average against peer data as per segment comparison, for social need, thus car owners will have greater satisfaction when emulating their peers, although this has a low weighting (see Table 3.10). In the car selection algorithm, each owner cycles through the different purchase options; imitators will prioritise finding a car using the same purchase option as their peers, optimisers prioritise their previous purchase strategy whilst deliberators will consider all options equally.

3.8 *Consumat* agents

In this section, the functionality of the *Consumat* agents is described, each of which is permanently linked to one car owner and acts as its decision making agent.

3.8.1 Communications

Consumats receive communications from their parent car owner, peers and the media agent and can also communicate directly with the car maker agent when deliberating.

When a message is received from the media agent (see 3.4), the *Consumat* adds it to its media memory and removes the oldest memory item where necessary to maintain a maximum of 10 items. The *Consumat* then updates its aggregate knowledge of the car market. This takes the form of a matrix with the current minimum, maximum, average, exponentially weighted moving average (EWMA), variance and exponentially weighted moving variance (EWMV) of each item. For those items with discrete values where a mean is not relevant (see Table 3.9), the mode is used and variance replaced by the ratio of the number of different values to the number of values in memory.

When information is received from a peer, this is used to update the peer memory and associated aggregate peer data in the same manner.

The parent car owner collects data on costs and range satisfaction and sends these to its associated *Consumat* each month. A simplified aggregate dataset using only the car owner's personal experience is collated.

Table 3.9: Aggregation of incoming data

Measure	Mean	Mode
Aspiration	1	0
Reliability	1	0
Range	1	0
Maintenance Cost	1	0
Tax Cost	1	0
Energy Cost	1	0
Total Cost	1	0
Emissions	1	0
Performance	1	0
Segment	0	1
Power Train	0	1
Purchase Type	0	1

3.8.2 *Consumat* state evaluation

Each month every car owner initiates a *Consumat* state evaluation process. Each of the personal experience values is compared to the aggregate data according to the processes described in Table 3.10 to produce an index between 0 and 1. For example the existence need component for Reliability will be based on the unmodified index sent to the *Consumat* by the car owner, whereas the social need component for Range will compare the range of the car owners current car to the minimum, maximum and simple average of their peers cars, returning an index using a sigmoid function. Where an Exponentially Weighted Moving Average (EWMA) is specified, this is calculated according to Equation 3.14 [136].

$$\bar{x}_t = \bar{x}_{t-1} + A\left(x_t - \bar{x}_{t-1}\right) \tag{3.14}$$

where

$\bar{x}_t$	=	Exponentially weighted moving average of x at time t
$\bar{x}_{t-1}$	=	Exponentially weighted moving average of x at time t-1
A	=	Alpha value = 0.1
		(determines weighting of historic data vs new data)
x_t	=	Value of x at time t

Each car owner was assigned a set of weightings ($W_{1...n}$ see Table 3.10) that represent how importantly they view each index. The owner's overall vehicle

Table 3.10: Evaluation types and weights

		Invert	Existence Need		Social Need		Personal Need	
i	Measure	$f_{u,i}$	$f_{e,i}$	$W_{e,i}$	$f_{s,i}$	$W_{s,i}$	$f_{p,i}$	$W_{p,i}$
1	Aspiration	-1	-1	0.00	6	*	6	*
2	Reliability	1	0	1.00	-1	0.00	2	0.50
3	Range	1	0	0.50	6	0.75	-1	0.00
4	Maintenance Cost	-1	1	0.50	-1	0.00	-1	0.00
5	Tax Cost	-1	1	0.25	-1	0.00	-1	0.00
6	Energy Cost	-1	1	0.50	2	0.25	-1	0.00
7	Total Cost	-1	4	1.00	2	0.25	-1	0.00
8	Emissions	-1	-1	0.00	2	*	10	*
9	Performance	-1	-1	0.00	6	*	10	*
10	Segment	0	-1	0.00	11	0.75	-1	0.00
11	Power Train	0	-1	0.00	11	0.75	9	0.75
12	Purchase Type	0	-1	0.00	11	0.25	-1	0.00

* indicates item individually set for each agent

–

Type Key ($f_{\alpha,i}$):

-1 = indicates not used in needs set

0 = do nothing to value

1 = convert to index relative to media using EWMA, min, max and sigmoid()

2 = convert to index relative to peers using EWMA, min, max and sigmoid()

4 = convert to index using personal comparator (compare to target/max limits)

6 = convert to index relative to peers using simple average, min, max sigmoid

9 = compare to last car

10 = compare to media where modal average is used

11 = compare to peers where modal average is used

12 = compare to all known data where modal average is used

–

Invert Key:

0 = ignore

-1 = reverse [$x' = (1 - x)$: lower value considered better]

+1 = do not reverse [$x' = x$: higher value considered better] satisfaction index was calculated as the weighted average of the individual indices. Thus the need satisfaction, S_α for any given agent is given by Equation 3.15.

$$S_\alpha = \frac{1}{n}\sum_{i=1}^{n} f_{u,i}(W_{\alpha,i} \cdot f_{\alpha,i}(M_{r,i})) \tag{3.15}$$

where

S_α	=	agent need satisfaction, $\alpha \in (e,s,p)$
$f_{u,i}$	=	function to invert index as set out in Table 3.10
$f_{\alpha,i}$	=	function to convert raw measure value as set out in Table 3.10
$M_{r,i}$	=	raw value of measure received from car owner by consumat
$W_{\alpha,i}$	=	weight applied to this measure as set out in Table 3.10

In addition to the satisfaction rating, a covariance value for each driver is also determined; this represents how similar the driver is to their peers or media depending on the need being evaluated (refer to Table 3.10) . Each month an exponentially weighted moving variance for each measure is determined using the same comparators as set out in Table 3.10. Equation 3.16 sets out the calculation. The driver covariance for each parameter is determined using Equation 3.17 where a true mean is possible or Equation 3.18 where discrete values are present and a modal average is used. A weighted average covariance is subsequently determined using the same approach as Equation 3.15.

$$\sigma^2_{\alpha,i,t} = \sqrt{A(m_{\alpha,i,t} - \sigma^2_{\alpha,i,t-1})(m_{\alpha,i,t} - \sigma^2_{\alpha,i,t}) + (1-A)\sigma^2_{\alpha,i,t-1}}^{\,2} \tag{3.16}$$

$$C_{\alpha,i,t} = \sqrt{\frac{\sigma^2_{\alpha,i,t}}{\sigma_{\alpha,i,t}}} \tag{3.17}$$

$$C_{\alpha,i,t} = \sqrt{\frac{\delta_{\alpha,i,t}}{\rho_{\alpha,i,t}}} \tag{3.18}$$

where

$\sigma^2_{\alpha,i,t}$	=	variance in need α, measure i, at time t
A	=	moving variance alpha value (A=0.1)
$m_{\alpha,i,t}$	=	value of converted measure i in need α at time t
$C_{\alpha,i,t}$	=	covariance value for measure i in need α at time t
$\delta_{\alpha,i,t}$	=	number of different values presented across peers or media (refer to Table 3.10, $f_{e,i}$)

Table 3.11: Needs measures and weighting

Measure	Existence Need	Social Need	Personality Need
Pert Minimum	0.50	0.25	0.25
Pert Mode	0.75	0.50	0.50
Pert Maximum	1.00	1.00	0.75

$\rho_{\alpha,i,t}$ = total number of peer or media memory items

Overall satisfaction and co-variance is determined from a weighted average of existence, social and personality needs as per Equation 3.19 (S being replaced by C for covariance). In the absence of survey data, the weights for each car owner were randomly assigned using a PERT distribution for each as shown in 3.11. The selection of these values was based on delivering a reasonable match to real world parameters, such as car ownership durations.

$$S = \frac{\sum_{\alpha=1}^{3} s_\alpha w_\alpha}{\sum w_\alpha} \tag{3.19}$$

Driver state change triggers

The overall satisfaction and covariance variables are used to trigger state transitions of the *Consumat* according to their individual satisfaction and uncertainty thresholds; see Figure 3.15.

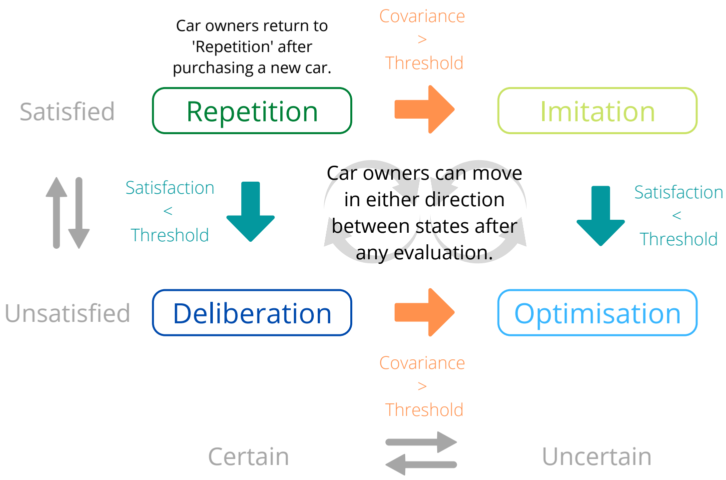


Figure 3.15: Car owner states and transitions

The satisfaction threshold for individual agents, i.e. the weighted needs satisfaction below which the agent's *Consumat* state moves from repetition to deliberation is set randomly using a PERT function with a minimum of 0.25, mode of 0.4 and maximum of 0.5. These figures were chosen based on observation of the range of weighted values achieved in the model.

The covariance threshold, i.e. the weighted covariance above which the agent's *Consumat* state moves from repetition to imitation or deliberation to optimisation were correlated to the consumat's income and education. This is based loosely on work by Morton et al. [153] where a positive correlation is shown to exist between both education and income level and the likelihood of adopting innovations. In this simulation, increasing the covariance threshold for more wealthy and educated individuals will tend to cause those agents to deliberate and explore new innovations when they seek a new car rather than consider only those their peers have adopted (i.e. they become early adopters). Morton et al. also identified a negative correlation of innovativeness with age; however, since agents do not age within the model, this is excluded.

If a car owner's car is written off or they dispose of the car due to budget constraints, then the agents satisfaction index is reduced to zero resulting in a deliberation or optimisation.

3.8.3 *Consumat* decision process

If the car owner has owned the car for over 3 months and the *Consumat* state is not repetition, then a state transition caused by the monthly evaluation will trigger an evaluation of available vehicles. Note that if the *Consumat* state is 'repetition' and the owner has a lease that has reached the end of its term, they will automatically replace their car with a new one of the same type provided that model is still available.

To reduce the set of cars to be searched, a simple screening of all cars in the market is undertaken prior to evaluation. This comprises the following tests and produces the set of 'suitable' cars referred to in the description following:

- capital cost or deposit <90% of car owners current savings balance + equity in existing car
- estimated cost per km + finance cost where applicable <monthly budget
- range >minimum range target
- car age <age of existing car on purchase + 2-[aspiration index weight] + number of months without a car.
  This function ensures that the car owner buys a car that is never more than 2 years older than their current car was on purchase, but those with high aspirational weight will tend to only consider newer cars. However, if the person is unable to find a suitable car, their acceptable car age will increase allowing a greater range of lower cost vehicles to be considered.
- a car that is not in the smallest 'micro' category if the car owner has children.

Any car model that does not meet the car owners minimum range requirement has its 'low_range' variable incremented. The car manufacturer agent uses this information to choose which car types to 'upgrade' to longer range after a defined date in simulations where this function is employed, see 3.3.2.

Imitation: satisfied and uncertain

The objective of an 'imitating' car owner is to replicate what their peers are doing within their own needs constraints. The following steps occur for an 'imitating' agent:

1. A memory set containing all the consumat's personal memory and the data received from peers is created.
2. A loop through each purchase type (purchase, lease, loan) is started using the most common purchase type of peers as the starting option.
3. A sub-set of suitable cars given this purchase type is generated.

4. A loop through the suitable car set is initiated.
5. A set of comparison data for the car under consideration is generated by obtaining the average of the memory set (step 1) for cars of the same power train.
6. A satisfaction index based on the comparison data is generated using the same function as Section 3.8.2.
7. If this car model is owned by a peer with satisfaction >0.6, meets the brand and segment loyalty requirements and has a higher satisfaction than all previously tested cars it will be held in memory. (An imitator may select a car with lower satisfaction than their existing car since, being like their peer's cars it is likely to result in lower variance.)
8. If a suitable car has been found at the end of the primary purchase type loop then this car is selected for purchase, otherwise the next purchase type is considered.
9. If no suitable car is found, then the owner will continue driving the same car until the next evaluation.

Optimisation: unsatisfied and uncertain

'Optimisers' are cognisant of both their peers and media information they've received, but do not carry out a full evaluation of all vehicles available. The following steps occur for an 'optimising' agent:

1. A memory set containing all the consumat's personal memory, the data received from peers and any media information is created.
2. A loop through each purchase type (purchase, lease, loan) is started using the car owner's previous preferred purchase option as the starting point.
3. A sub-set of suitable cars given this purchase type is generated.
4. A loop through the suitable car set is initiated.
5. A set of comparison data for the car under consideration is generated by obtaining the average of the memory set (step 1) for cars of the same power train.
6. A satisfaction index based on the comparison data is generated using the same function as Section 3.8.2.

7. If this car model is owned by a peer with satisfaction >0.6 or is not owned by any peer, meets the brand and segment loyalty requirements and has a higher satisfaction than all previously tested cars it will be held in memory. Optimisers do not require an estimated satisfaction index greater than their existing car.
8. If a suitable car has been found at the end of the primary purchase type loop then this car is selected for purchase, otherwise the next purchase type is considered.
9. If no suitable car is found, then the owner will continue driving the same car until the next evaluation.

Deliberation: Unsatisfied and Certain

A 'deliberating' car owner seeks to maximise their satisfaction index across all vehicles available in the market, whilst taking into account social preferences. The following steps occur for an 'deliberating' agent:

1. A loop through each purchase type (purchase, lease, loan) is started using the car owners previous preferred purchase option as the starting point.
2. A sub-set of suitable cars given this purchase type is generated from the entire set of cars in the market.
3. A loop through the suitable car set is initiated.
4. A set of indices is created for the car using car owner specific data and car manufacturer performance data over a term of 3 years, including a TCO for operating cost (Table 3.2)
5. The expected Existence Need and Personality Need satisfaction indices are set by comparison of the car to all cars in the market as Section 3.8.2.
6. The expected Social Need satisfaction index is set by comparison to peer knowledge.
7. If this car model meets the brand and segment loyalty requirements and has a higher satisfaction than the owners existing satisfaction and all previously tested cars it will be held in memory.
8. The next purchase type is considered.

9. The best performing car overall (any purchase type other than Company Lease) will be selected.
10. If no suitable car is found, then the owner will continue driving the same car until the next evaluation.

3.8.4 Car selection completion

If a car has been selected, then the *Consumat* state returns to 'Repetition' and the car owner's satisfaction index is set to 0.9 and uncertainty index to 0. The selected car is returned to the car owner agent via a function call either as a new purchase or exchange. The car owner's budgets, finance data and other car associated cost data are reset for the new vehicle and the owner continues making normal journeys.

3.9 Car agents

This section describes functionality associated with car agents and subsidiary battery agents where applicable.

3.9.1 Journey functions

Figure 3.16 illustrates all possible car states in the model. When cars are generated by the model, they start their life in state 'AtNewCarDealer', on purchase they move to the 'InUse' super-state 'Parked' Condition. If the car is unsold after 1 year, it moves to the 'AtUsedCarDealer' state from where it can also be purchased and move to the 'Parked' condition. When a journey is initiated by the car owner, the average speed and consequent fuel consumption is determined [134] and a transition to state 'BeingDriven' occurs. A timed event is scheduled to trigger the next state transition depending on the type of vehicle and fuel/charge state:

- All cars with sufficient charge/fuel for journey: return to 'Parked'
- ICE (including HEV) with insufficient fuel: 'FillUp'
- PHV with insufficient charge: 'PHVSwitch', car switched to fuelled mode (may result in subsequent 'FillUp' event depending on fuel level)
- BEV with insufficient charge and charger available in range: 'Queuing' and on to 'FastCharge'

- BEV with flat battery: ‘LowSoC’ and on to ‘FastCharge’

All cars may also have a latent breakdown pending, which results in a transition to ’Breakdown’ state, or may be written-off due to an accident causing a transition to ’Scrapped’ state. The rate of write off is based a 2017 survey by Churchill Insurance in the UK [36].

On journey completion, all cars enter the ‘Parked’ state and chargeable cars (BEV and PHV) may then make further transitions. In the base analysis, owners with access to home charging remain in the ‘Parked’ state if they are not at home and have sufficient charge to complete their next journey. In all other cases the car owner action is determined by locational charger availability (see Section 3.5) and cars will move into the holding state for that charging type as soon as they are ‘parked’. For the base analysis, the only state considered is ’Uncontrolled’, and here cars move directly on to ‘ChargingU’ state when their SoC is below 100%. If the charge is completed before the next journey is initiated, the car moves back to the ‘Uncontrolled’ state and waits for the next journey to be initiated. If the charge is not complete, then the car will move directly from the charging state to ‘BeingDriven’.

The charging algorithm for each charge mode will determine the start-time and end-time of the charge based on the battery capacity, SoC and charge rate, which is 7.4kW in the base case. This is the normal AC charge rate for most modern EVs and is based on a 32A charge at ca. 230V. A charging efficiency of 85% is assumed based on work by Kieldsen et al. [126] and analysis by PushEVs [138]. Rapid chargers charge at an increasing rate over time, subject to a vehicle imposed limit as described in 3.5.1; this approach is also adopted for destination rapid chargers.

3.9.2 Energy costs

A base fuel efficiency is defined for each vehicle as per Table 3.2. This efficiency is adjusted for each journey based on the mean journey speed. Figure 3.17 illustrates that, for EVs, the speed of travel has a much more significant impact on energy consumption than in ICE vehicles since fixed losses are particularly small, making aerodynamic losses dominate.

The NTS data comprises some 446,034 car trip stages. For each stage, the distance and time taken are presented and each stage is also allocated a group based on the distance travelled. Figure 3.18 plots the mean, minimum and maximum speeds recorded for each journey against the mean distance for the band. It is clear from this analysis that, whilst short journeys are, on average, undertaken at lower speeds, some relatively short journeys (falling into the bands for distances

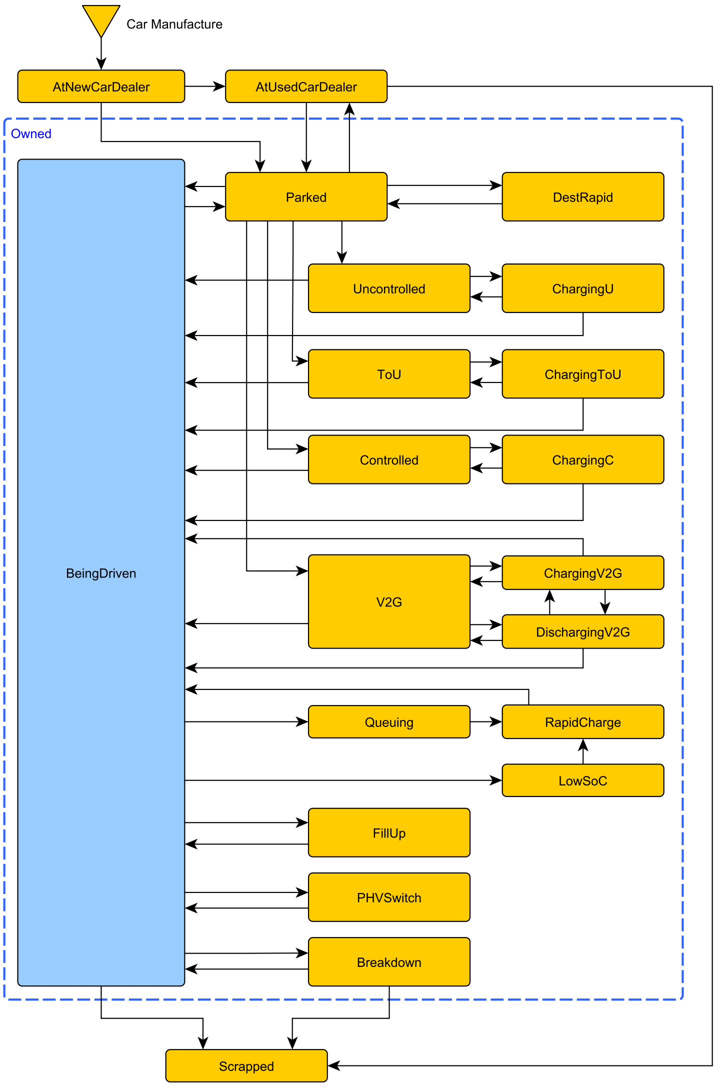


Figure 3.16: Car function state chart showing all possible states of a car, regardless of power train.

greater than 5km) may be undertaken at the same average speed as much longer journeys. This effect is modelled in the simulation by assigning each journey to an NTS band and then determining a speed. The band is determined from a look-up table and the speed is then set using a PERT distribution with minima, maxima and mode set by the in-band data as shown in figure 3.18. For PHVs in electric mode and BEVs, the mean power consumption during a journey is estimated by adjusting the specified efficiency (Table 3.2) by a factor determined from Figure 3.17 as described by Equation 3.20. For ICE vehicles, the specified fuel efficiency is adjusted in a similar manner according to equation 3.21.

$$P_u = \frac{u}{\frac{\eta_c}{\eta_0} f_{EV}(u)} \tag{3.20}$$

$$\eta_u = \frac{\eta_c}{\eta_0} f_{ICE}(u) \tag{3.21}$$

where:	u	=	mean journey speed
	P_u	=	EV power consumption at speed u
	η_u	=	ICE efficiency at speed u
	η_c	=	efficiency of car from Table 3.2
	η_0	=	efficiency of reference car used in Figure 3.17
	f_{EV}	=	Figure 3.17 Tesla curve
	f_{ICE}	=	Figure 3.17 ICE curve (converted to l/100km)

At the end of each journey, or journey stage where refuelling/recharging is required, the fuel tank level and/or SoC of the vehicle is adjusted according to the efficiency determined from the speed estimation. Fuel tanks are refilled only during journeys and the cost is accrued to a monthly total. For rechargeable vehicles, in-transit recharges are costed at the rapid charger tariff (see 3.1), but otherwise cars are charged when parked according to the tariff prevalent at the location. Charging costs are also accrued to a monthly account. Refuelling/recharging costs are deducted from the car owners savings balance at the end of each month.

3.9.3 Tax costs

Vehicle tax costs are incurred once per year, based on the tax regime defined by the main agent, and deducted from the car owners savings balance at the end of the month in which they are incurred. For company car owners, the tax cost incurred as a result of BIK rate is charged to the savings account monthly. Tax costs to 2022 are based on actual policy, thereafter, the base case assumes no change in policy.

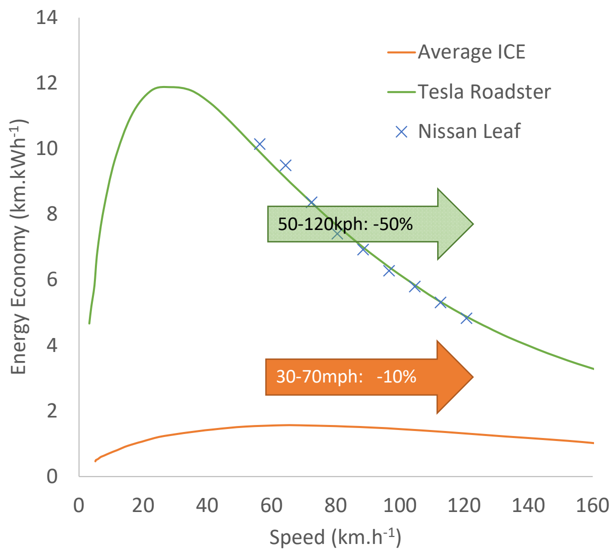


Figure 3.17: Energy economy of average ICE vehicle [28] compared to Tesla Roadster [206] and Nissan Leaf [76] showing significance of speed for EVs.

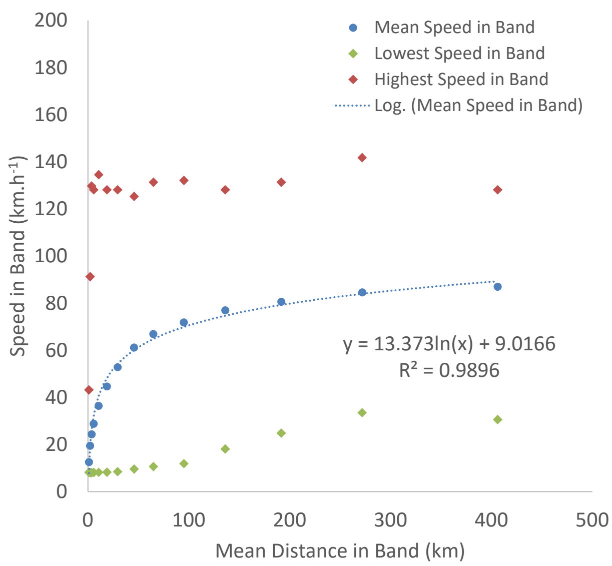


Figure 3.18: Mean, minimum and maximum speed vs average distance in stage length band. Bands are as defined in NTS data protocol.

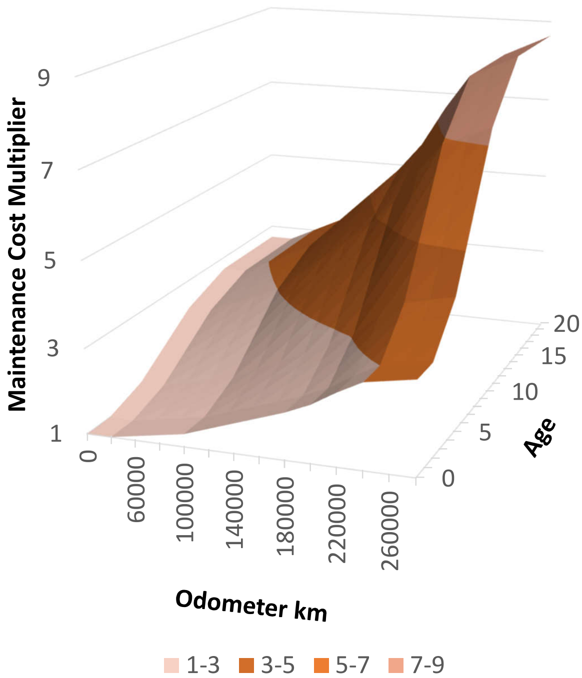


Figure 3.19: Maintenance multiplier applied to year 0 maintenance cost based on age and odometer reading of car

3.9.4 Maintenance costs

Car maintenance costs are set in the first year ($C_{m,0}$) from the value in table 3.2. This figure is a function of the initial vehicle cost ($C_{c,0}$) and fuel train type according to Equation 3.22

$$C_{m,0} = \begin{cases} C_{c,0} \times 0.01 & \text{carType} = PET \text{ OR } DIE \\ C_{c,0} \times 0.015 & \text{carType} = HEV \text{ OR } PHV \\ C_{c,0} \times 0.0025 & \text{carType} = BEV \end{cases} \tag{3.22}$$

The actual maintenance cost is further limited between £60 and £900 per annum. These Figures are based on indicative vehicle maintenance costs from [145], which indicate that luxury brands (higher purchase price) cars are generally more expensive to maintain. Where actual maintenance costs could be sourced, these were used.

The frequency of breakdowns was determined from analysis of failure rates with reference to car age and mileage using data sourced from German TUV/Autobild survey data [214]. Failure rates against distance and age are shown in Fig-

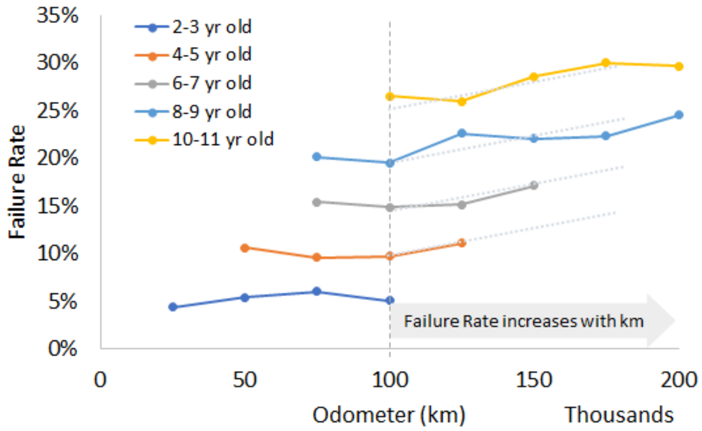


Figure 3.20: Failure rate of cars grouped by age vs km travelled, showing that failure rates appear largely independent of km travelled below 100,000km, but increase with distance after that.

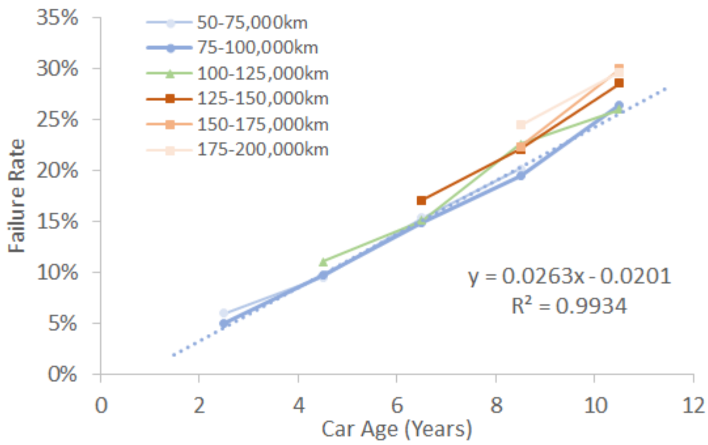


Figure 3.21: Failure rate of cars grouped by km travelled against age

ures 3.20 and 3.21. It can be seen that up to 100,000km, failure rate is dominated by car age, but beyond this, distance travelled also contributes. The data available does not disaggregate power train types and whilst there is some evidence, and justification in there being far fewer moving parts, that BEVs are more reliable than conventional vehicles, no differentiation is included in the model.

The actual failure rate is thus determined according to Equation 3.23. The cost of the breakdown is set according to Equation 3.24, such that the maintenance cost over an operational year is approximately equal to the average value of $C_{m,t}$ over the period regardless of the expected number of breakdowns.

$$\lambda_{s,t} = \begin{cases} 0.0263t - 0.02, & s < 100\,000 \\ 0.0263t + 3.5 \times 10^{-7}s + 0.15, & s \geq 100\,000 \end{cases} \tag{3.23}$$

$$C_{m,t} = C_{m,t-1} + \frac{2U[0, C_{m,y}]}{\lambda_{s,t}} \tag{3.24}$$

where:

$\lambda_{s,t}$	=	failure rate (per year) at distance s and time t
$U[0, C_{m,y}]$	=	sampled uniform distribution between 0 and year y maintenance cost

Cars also undergo scheduled maintenance at the year 0 maintenance cost defined in Table 3.2. The model assumes all cars are maintained annually or at 15,000km intervals, whichever occurs first. In practice, some EVs do not require annual servicing, but the maintenance cost is adjusted down to reflect an annual service cost.

Car end-of-life

Cars can be scrapped, and removed from the simulation, either when they are unsold in the used car market and their age is more than 20 years or with a probability increasing with age on breakdown. Any car less than 15 years old will be repaired, but older cars will be scrapped on breakdown with a probability increasing linearly from 0 to 1 as the car ages from 15 to 20 years. On scrapping, the car owner is left without a car and moves into an evaluation state, examining available cars for purchase each week.

3.9.5 Car depreciation

The value of each car in the model was depreciated according to Equation 3.25.

$$C_t = \begin{cases} t < 1 & tD_{y1}C \\ t >= 1 & D_{y1}C + (t-1)D_{yn}C - k(s_m - s_0) \end{cases} \tag{3.25}$$

where:

C_t	=	depreciation at time t (years)
D_{y1}	=	year 1 rate of depreciation
C	=	cost of car when new (GBP)
D_{yn}	=	rate of depreciation from year 1 onwards
k	=	odometer adustment factor (0.06GBP/km)

s_m	=	mean distance travelled (km)
s_0	=	base km (at which only time depreciation is applied)

Each car in the model has a different depreciation rate which is based on figures for similar vehicles from [176]. Where depreciation rates were not available (e.g. for cars introduced from 2019 onwards), year 1 depreciation is set to 25% and subsequent years to 10%.

3.9.6 Car aspiration index

Each car is assigned an aspiration index that declines over time. The initial aspiration index is the same for all vehicles in a market segment; it is constrained between 0 and 1 and set to the purchase cost of the most expensive car in the segment divided by £75,000. This gives the "sports cars" segment an aspiration index of 1 and the "mini" segment (such as a Citroen C1), an index of 0.12. The aspiration index at time t is adjusted according to Equation 3.26. The range related adjustment is designed to reduce the desirability of cars with a range less than the mean range of recent vehicles, but to remove range as a factor in desirability for all but the lowest range ICE vehicles.

$$I_{a,t} = I_{a,0} \times (1 - D_a)^{max[0, A_t - A_0]} \times min\left[1, \frac{R}{min\,(R_m, 600km)}\right] \tag{3.26}$$

where:

$I_{a,t}$	=	aspiration at time t (years)
$I_{a,0}$	=	base aspiration index for segment
D_a	=	aspiration annual depreciation fraction
A_t	=	Age of car at time t (years)
A_0	=	age at which depreciation commences (years)
R	=	vehicle range (km)
R_m	=	mean range of vehicles less than 5 years old (km)

Figure 3.22 illustrates how the aspiration index would vary with car age for two ICE cars and two BEV cars.

3.10 Battery agents

Battery agents are created whenever a car with a chargeable battery is made (BEV or PHV). State transitions of the parent car agent will result in charging functions being triggered in the battery agent and the battery agent triggers charge

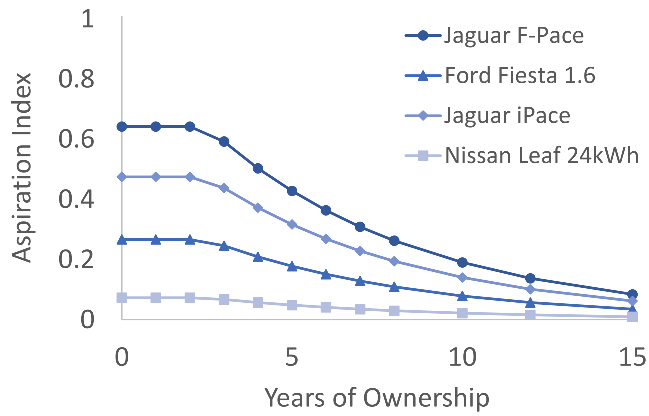


Figure 3.22: Example of aspiration index for various cars and change over time

completion events in the associated car agent. The battery agent also triggers the transition to the 'LowSoc' event for its parent car.

3.10.1 Start driving

On the transition to 'BeingDriven', the car agent triggers a function in the battery agent which calculates the battery discharge rate based on the trip speed and ancillary power [134] and schedules two events:

1. Stop battery use event. Scheduled to occur when battery will reach minimum SoC and initiates a 'LowSoC' transition by the parent car.

2. Seek rapid charge event. Scheduled to occur when the car would be left with 20km range (based on efficiency) and initiates a search for a rapid charger (Section 3.5)

If a rapid charge is found within the minimum range, then the events are rescheduled and the journey continues following a charge to 80% of battery capacity, which is the norm for rapid charging due to reduced charge rate above 80%. If no rapid charger is found, then the 'LowSoc' transition will occur and a rapid charge will be initiated after a delay set by an exponential distribution with rate of 0.5 per hour. Note that if the Seek Charge event is triggered, but the car is able to reach its destination (i.e. <20km) it will continue to the destination.

All en-route charging events are assumed to be rapid chargers which will charge at a maximum rate limited by the car or the available charging rate of the charger (Section 3.5). This is a simplification of real-life charging rates, which are dependent on, inter alia, battery SoC and temperature.

3.10.2 Stop driving

At the end of each drive, the car agent will initiate the stop driving function. This stops the battery discharge and cancels all other scheduled events. The battery stored kWh data is updated together with a remaining range. The battery cycle count is also incremented according to the percentage of SoC consumed and an exponentially weighted moving average car efficiency (km/kWh) is updated. In addition, a simplified battery degradation function is called.

3.10.3 Battery degradation

Degradation of Lithium-Ion batteries is known to be of concern to EV purchasers [124] and such concerns are likely to be exacerbated by V2G applications even though such use is not expected to contribute significant degradation [234]. Whilst there is a significant body of literature concerned with lithium ion battery degradation, little of this focuses on real-world EV use, and that which does tends to reflect older EVs (both BEVs and PHVs) with smaller batteries, often without thermal management, that tended to exhibit more rapid degradation than newer models. There are a number of resources exploring real-world battery degradation, particularly for Tesla Model S and Nissan Leaf vehicles which have been present in the market since 2012 [204]. GeoTab, a Canadian Company that provides fleet vehicle solutions globally, including monitoring able to record battery SoH, also provides publicly available degradation data based on vehicle age [96]. Averaged across all vehicles, the GeoTab data indicates a linear reduction in capacity with age. However, this is based on readings from the EV CanBus system (direct readings from the Battery Management System (BMS)), which are not normally visible to the car owner and do not take into account the margin between battery pack size and usable capacity adopted by EV manufacturers [84]. This margin tends to disguise the initial degradation, such that cars will typically show no reduction in range during initial ownership even though actual battery SoH will have reduced. A detailed battery degradation model is beyond the scope of this simulation, and thus a simplified approach has been adopted that takes into account the usable capacity and the impact of larger batteries, resulting in reduced cycles for the same mileage.

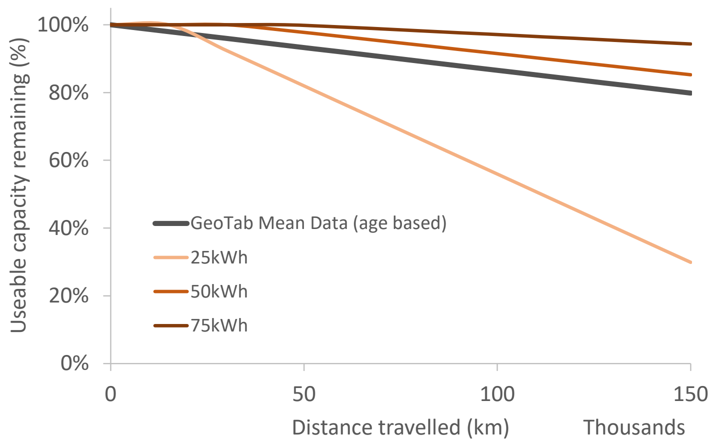


Figure 3.23: EV battery degradation based on data from [96] modified to a cycle-based rate assuming 15,000km/year and 6.4km/kWh efficiency and accounting for battery size.

A simplified degradation function using equation 3.27 is implemented in the simulation. Figure 3.23 shows the average GeoTab [96] battery degradation based on an assumed 15,000km per year driving distance, assuming a spread of vehicles from North America, where annual mileage averages 18,000km [86] and Europe 12,000km [168] and a typical EV efficiency of 6.4km/kWh. The modelled degradation is illustrated for three hypothetical batteries of 25, 50 and 75kWh capacity. The 24kWh Leaf, being close to the 25kWh example, is indicated as having around 90% capacity after 3 years for a UK sample [204], which here would correspond to 35,000km, and is a reasonable match given average UK annual car mileage of 12,000km. The Tesla model S, 60kWh data [204] indicates about 90% SoH at 130,000km; the function used here would also return 90% SoH at this distance.

$$E_t = \begin{cases} C_t < C_0 & E_0 \\ C_t >= C_0 & E_0 - D(C_t - C_0) \end{cases} \tag{3.27}$$

where:

where:	E_t	=	energy capacity at time t
	C_t	=	completed whole cycles at time t
	C_0	=	whole cycles after which degradation begins, set at 100
	E_0	=	energy capacity when new
	D	=	degradation rate (set at 0.02kWh/cycle)

3.10.4 Charging data

When the car agent initiates a destination charging event, the battery agent sets the charge rate, according to location, and schedules an event to terminate the charge when an SoC of 100% is reached. Whilst charging is in progress, an event scheduled at the end of every 30 minute trading period updates an energy total and household demand (if charging at home). These totals are aggregated by the main agent for reporting purposes.

3.11 Model enhancements

This section describes modifications made to the model following validation to enable refine forward projections and enable various policies and charging strategies to be simulated.

3.11.1 Car depreciation

Some policies, such as vehicle bans, and the introduction of longer range EVs might cause depreciation rates on some vehicles to change. This could impact adoption since both the initial TCO calculation for new cars and purchase prices for used vehicles would be affected. This is emulated by adjusting depreciation rates for each model based on the mean number of months they remain either in the new car market or used car market. Equation 3.28 is used for both year 1 and subsequent year depreciation rates, which are set differently for each model of car [133].

$$D_t = D_{t-1}\left(1 + \frac{\overline{T} - 6}{100}\right) \tag{3.28}$$

where:

D_t = Depreciation rate at month t
$\overline{T}$ = mean number of months car model has been on market

The period of 6 months for depreciation neutrality and 100^{th} factor were chosen heuristically to deliver realistic depreciation rates given the frequency with which car owners evaluate options and make purchases in the simulation.

3.11.2 Carbon emissions estimates

The simulation includes data on individual vehicle tailpipe emissions and also determines emissions from electric vehicles based on the electricity emissions coefficient as time progresses (see 3.3). Previous research on policy impacts has noted that scrappage schemes may not be beneficial due to embodied carbon from the manufacture of new vehicles, especially EVs [29]. However, this research was conducted in 2013 when grid emissions were nearly double the level in the UK today. More recent work on the embodied carbon in lithium-ion batteries is also showing a decrease. In a study by the Swedish Environmental Institute, IVL [79], they revised their 2017 estimate of 150-200kgCO_2e kWh^{-1} down to 61-106kgCO_2e kWh^{-1} in 2019, for the most common EV battery chemistry (Nickel-Manganese-Cobalt, NMC) based on a meta study of more recent Life Cycle Assessments. A Union of Concerned Scientists report [160] identifies a mid size vehicle, whether electric or ICE, as having an embodied carbon, excluding the battery in the case of EVs, of about 7,500kgCO_2e. Whilst the simulation includes both smaller and larger vehicles, which will have differing embodied carbon, there is no reason to suspect that the distribution of vehicle sizes will change as a result of electrification, so it is reasonable to assume that a figure of 7,500kgCO_2e can be applied as a fleet average. To provide a simplified assessment of the carbon benefit of policy scenarios, each car is assigned an embodied carbon of 7,500kgCO_2e plus 100kgCO_2e $kWh^{-1} \times [batterysize]$kWh. Figure 3.24 illustrates the relative embodied emissions of ICE vehicles and BEVs with various battery sizes and provides an indicative life-cycle emissions estimate based on 150,000km and UK Government reporting figures for emissions [107]. The simulation determines the total embodied carbon in new cars created (excluding those initialised at the start of the model) and the emissions due to driving, which are adjusted for efficiency at average journey speed as described in Section 3.9.2. The emissions coefficient for EVs is reduced over time in accordance with Figure 3.3. The car fleet mileage is accrued and and average fleet emissions factor calculated at each reporting interval. Figure 3.25 provides an example of the output across the fleet.

3.11.3 Controlled charging algorithm

The basic charging options comprise immediate charging when arriving at a charge point (referred to as 'uncontrolled') and a ToU tariff, where charging commences at midnight and finishes at 7.00am, on the assumption that overnight demands are low. In this section, a simple controlled charging algorithm, requiring no communications external to the vehicle, is introduced.

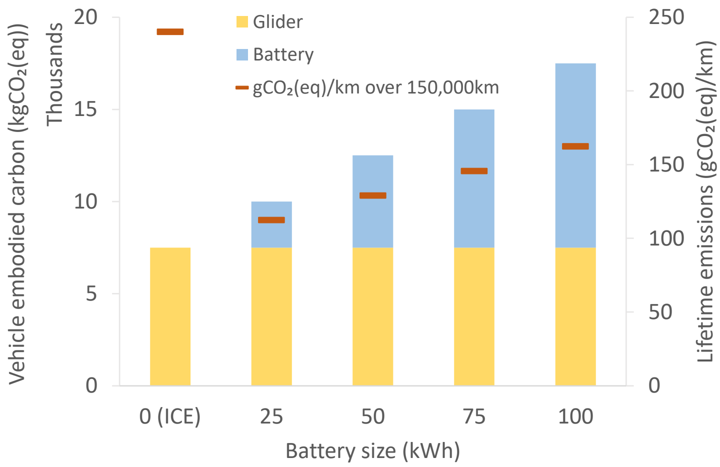


Figure 3.24: Simplified embodied emissions estimate for ICE and various battery sizes together with indicative per-km lifecycle emissions over 150,000km at EV as charged efficiency of 5.6km kWh^{-1} and 2019 UK grid emissions (0.2556kgCO_2e kWh^{-1} [107]) and medium-size petrol car emissions of 0.19228kgCO_2e kWh^{-1} [107].

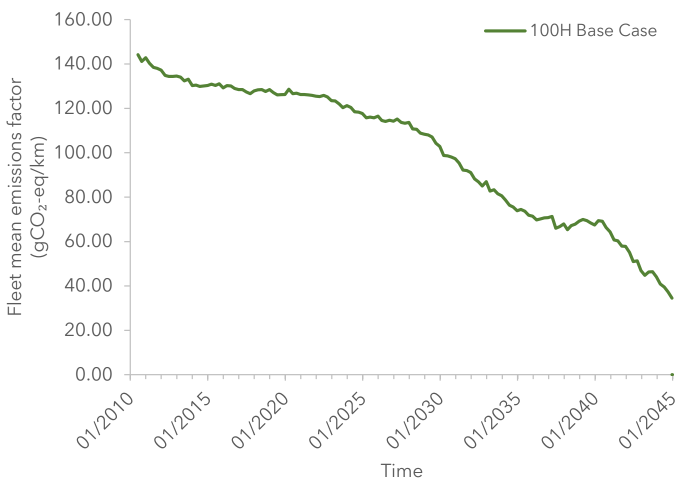


Figure 3.25: Example of Fleet emissions factor (for base case, 2040 ICE Ban) including allowance for embodied carbon in vehicles

The controlled charging algorithm seeks to charge all cars to a minimum of 80% SoC prior to their scheduled departure time and to do so outside of peak hours unless the car cannot achieve a minimum range of 100km. On parking and plugging in at a home charger, the time to charge is determined according to Equation 3.29 and the longest possible delay to the start of charging according to Equation 3.30. The actual delay is then determined from Equation 3.31, which was arrived at by trial and error to deliver a reasonably flat charging profile outcome across a test set of 100 vehicles. Uniform and normal distribution were also tested. A delay timer delays the transition of the EV from plugged in state to charging state by time t_d unless the stored charge results in a range at the current driving efficiency of under 100km. Charging is suspended whenever the base settlement profile for domestic consumers (Elexon profile 1, winter weekday [78]) exceeds 0.6kW and range is greater than 100km and is restarted based on recalculation of t_d.

$$t_{cmin} = \frac{0.8E_{max} - E_t}{P_h} \tag{3.29}$$

$$t_{dmax} = t_t - T_{cmin} \tag{3.30}$$

$$t_d = PERT(0, t_{dmax}, min[3.5h, \frac{t_{dmax}}{2}]) \tag{3.31}$$

where:

t_{cmin} = minimum time to complete charge
E_{max} = Energy capacity of fully charged battery
E_t = Energy capacity at current time, t
t_{dmax} = maximum delay time to start of charging
t_t = time to next trip
t_d = delay to start of charging
$PERT(min, max, mode)$ returns the PERT distribution for the given parameters

3.11.4 V2G algorithm

There are numerous ways in which V2G algorithms might work. In the analysis here, a relatively simple approach is adopted which can, in principle, be implemented 'in-car'. There are four outcomes from the charging algorithm:

1. Charge immediately if battery capacity less than required irrespective of grid status

2. Charge if battery capacity less than required and if grid generation > grid demand (grid frequency > 50Hz)

3. Discharge if battery capacity greater than required and grid demand > grid generation (grid frequency < 50Hz)

4. Do nothing

The simulation runs the algorithm for each BEV at a Poisson distributed rate of six times per hour whenever the car is connected at a V2G enabled charge point. Using a random interval ensures that, whilst cars make decisions independently of each other, large swings in demand are avoided and the decision is always based on a constantly evolving system balance. The first step is to determine the minimum power needed to achieve the required stored energy prior to the next scheduled departure as described in Equation 3.32. This value may be negative if the battery has more energy stored than is required. The operating mode of the car is then selected according to Equation 3.33. Whilst modes 1 and 2 result in the same action, they differ in subsequent functions in that a car in mode 1 cannot be switched from charging to idle or discharging since it must continue at power P_c in order to reach its SoC target prior to departure. When a change of mode occurs, the charging power (P_c) is added to P_d or P_g accordingly. Thus the next car to initiate a V2G assessment receives different generation and demand parameters.

$$P_{min} = \frac{\frac{1}{\eta}\left(s_d - s_{\Sigma d} + s_{d+1} + s_c\right) - E_b}{t_d} \tag{3.32}$$

where:

P_{min} = minimum power required to charge the car to the target level in the time available, t_d (k
η = Exponentially weighted moving average EV efficiency (km kWh^{-1})
S_d = Total NTS distance on current day, d (km)
$s_{\Sigma d}$ = Distance already completed on day, d (km)
s_{d+1} = Total NTS distance for following day, d+1 (km)
s_c = driver-specific comfort margin (km)
E_b = Energy stored in battery at time of evaluation (kWh)
t_d = time available until next scheduled departure (hours)

$$Mode = \begin{cases} 1, & P_{min} > P_c \\ 2, & (P_{min} < P_c) \wedge (P_g > P_d) \\ 3, & (P_{min} < -P_c) \wedge (P_g < P_d) \\ 0, & Else \end{cases} \tag{3.33}$$

where:

P_c = the charging power of the connection point (nominally 7.2kW) (kW)
P_g = Current generation including V2G discharge from other EVs (kW)
P_d = Current demand including household profile and EV charging (kW)
$Mode = 1$ Charge immediately
$Mode = 2$ Charge now (effectively same as Mode 1)
$Mode = 3$ Discharge now
$Mode = 0$ Do nothing

The non-V2G generation is updated at each change in trading period (every half hour). The data was sourced from [38] and comprises a 9 year normalized profile of wind and solar generation from the UK. The simulation applies a factor to the normalised generation such that the total generation in the year is approximately equal to 15% above the expected energy demand based on the number of households, all assumed to consume the Elexon profile 1 winter residential use (3,635kWh per year) [78], and the number of EVs in use, consuming an average of 1,835kWh per year. The installed generation capacity required to meet this is updated every month according to the number of EVs owned. 15% was selected as over-generation as suggested by Cardenas et al. [38].

Chapter 4

BEVI model validation

Agent-based models quickly become opaque to examination by those unfamiliar with the code and with many processes based on empirical observation, validation of the model is an important component in demonstrating its credibility [242]. In this chapter, a number of model outputs and relationships are presented to demonstrate that the simulation responds in the expected way and that it is able to reproduce historic car ownership patterns and current EV charging demands.

4.1 Trip analysis

To validate the approach taken to modelling drive cycles, Figure 4.1 compares the distribution of journey lengths generated by the model with the full NTS data set and the reduced sample of journeys used in the simulation.

The unplanned trip function in the model adds trips based on the distribution of journey lengths in the full NTS data, which can be considered a reasonable explanation as to why the model produces results closer to the full data set than the modelled sample. Without adding unplanned trips, the average distance a car travels per day in the model is 27.5km compared to a reported average of 34.4km from the NTS (7,800 miles per year). The parameters for unplanned journeys have been tuned in the simulation resulting in an average daily distance per vehicle of 35.1km.

4.2 Time of travel distribution

The NTS data includes an analysis of time of travel divided into weekdays, Saturdays and Sundays. Figure 4.2 compares this NTS data with the simulation results after one year. Here the NTS data, which has been averaged (using 5 x weekday

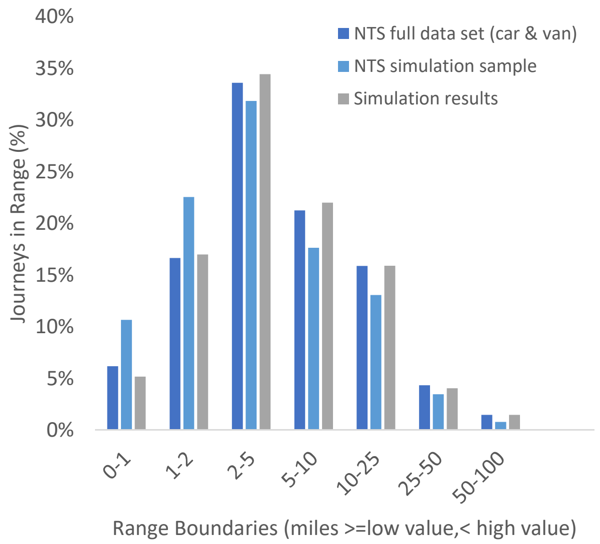


Figure 4.1: Comparison of NTS mileage and model mileage. Miles are used here because the original NTS data is analysed in mile-based ranges.

weighting) and compared to the average data from the model. This shows reasonable correlation across the day. The peak between 8am and 9am and evening tail of lower values from the simulation is a result of the method by which return trips from unplanned journeys are scheduled. The model schedules a return journey based on the hourly probability of a trip starting in the NTS data. Since an unplanned trip will generally start during peak hours, and the probability of a journey starting in the evening is low, this means that the return trip is most likely to be initiated either immediately following the outbound trip or in the peak travel hours the following morning.

4.3 Electric vehicle charging profiles

Figure 4.3 shows a sample week of BEV charging demand where 85 BEVs are charged at a rate of 3.6kW (common for older BEVs and PHVs) when parked at the owners home. If recharging is required during a journey, then a charge rate of 50kW is assumed; this accounts for the short-sharp peaks in the sample week. Figure 4.4 runs the same simulation with charging assumed at 7.2kW. The mean charge profile shows higher peaks for higher rate charging, as may be expected, but also shows charging falling to zero in the early hours of the morning, whereas charging continues throughout the night for some EVs at 3.6kW.

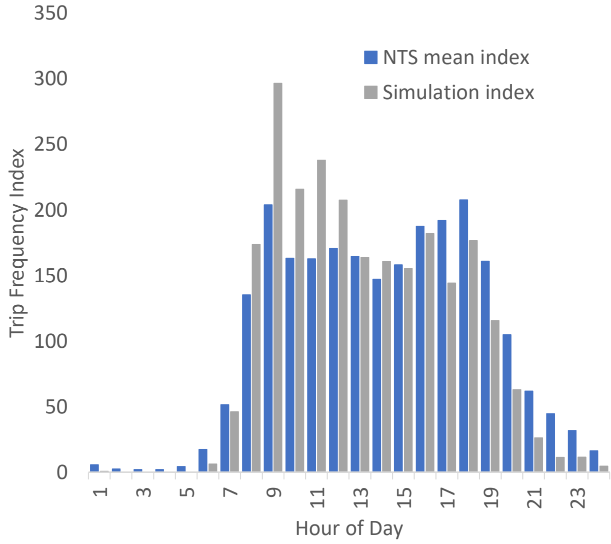


Figure 4.2: Comparison of NTS trip frequency analysis and simulation output. Here an index value of 100 corresponds to the average number of journeys commencing in each 1 hour period, therefore and index of 200 would indicate double the average number of journeys in that period.

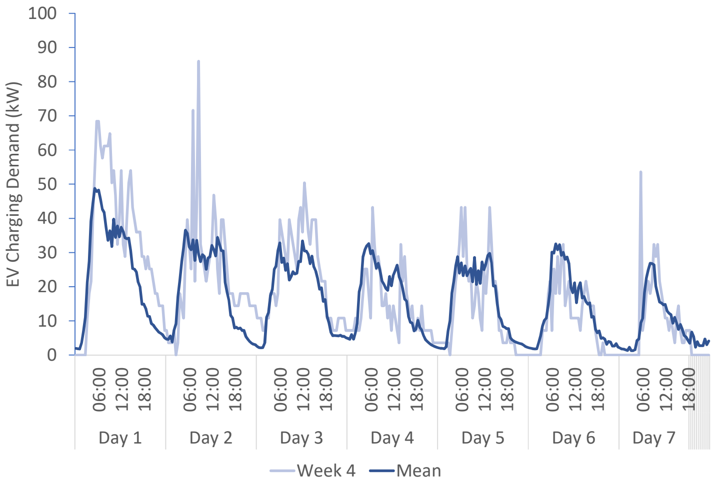


Figure 4.3: Sample week and annual mean charging profile for 85 BEVs being charged at 3.6kW (except fast charging at 50kW)

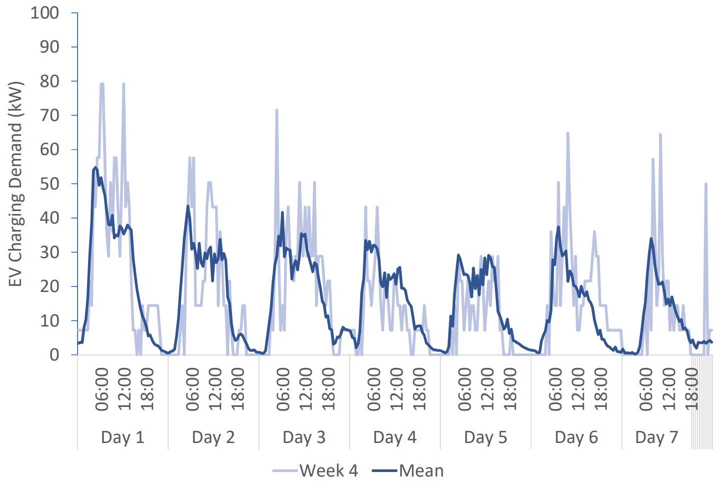


Figure 4.4: Sample week and annual mean charging profile for 85 BEVs being charged at 7kW (except fast charging at 50kW)

4.4 Preferences reflected in purchase decisions

In this section, a number of results demonstrating that the simulation approach is able to reflect constraints on car buyers and their preferences are set out. For this purpose, the focus is on the period of 25 years post-2012, when BEVs first enter the UK market, and a comparison of these to solely petrol or diesel internal combustion engine (ICE) vehicles. Both HEVs and PHVs, being of intermediate environmental benefit and cost, and requiring a less dramatic shift to the norm, tend not to be so clearly differentiated in purchase preferences. The number of BEV purchases in the early years is small: between 1 and 3 up to 2016 and does not exceed 100 until 2031, this compares with approximately 400 ICE purchases each year to 2020, as such volatility can be observed in the early-years BEV data.

4.4.1 Buyer greeness

Figure 4.5 illustrates the mean greeness index of ICE buyers and BEV buyers from the introduction of BEVs in 2012 to 2038. This indicates that car owners with a high greeness index are more likely to be EV purchasers, but overtime, the greeness of first-time BEV buyers decreases as BEVs become more commonplace. The oscillations in early years also show an interesting aspect; in the model, the gree-

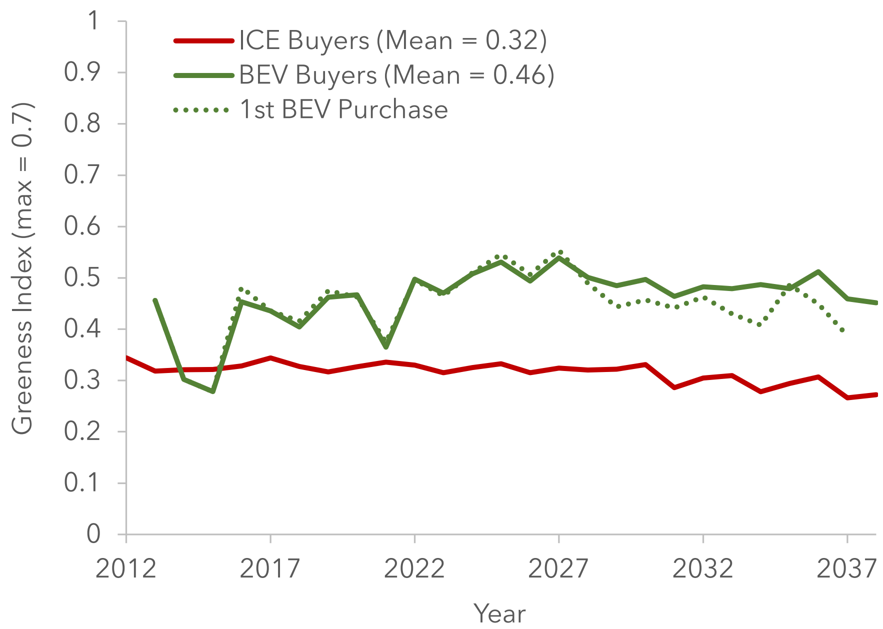


Figure 4.5: Mean 'greeness' weighting (max = 0.7) of BEV buyers and conventional ICE buyers over time. The dotted line indicates the greeness of first-time BEV buyers showing slight decline in greeness over time.

ness and performance weightings of drivers are loosely inversely correlated and examination of the data shows that early EV adopters with low greeness weights tend to be those with high performance weights, indicating an attraction to the impressive acceleration times available for EVs. The greeness of the buyer is however a significant influencer for early adopters suggesting that measures to increase the average level of environmental concern combined with clear demonstration of the carbon-footprint and local emissions benefits of EVs is likely to have a positive impact on uptake rates.

4.4.2 Buyer income

Figure 4.6 presents the mean monthly household income of BEV owning and ICE owning households over the modelled period. BEV buyers typically have a household monthly income some £600 greater than the average ICE buyer household in early years, reflecting the higher purchase price of BEVs. (n.b. the income here is higher than the UK average since it includes only those households that own cars.) As battery costs decline, and more used BEVs appear in the market, so the BEV buyer mean income approaches that of ICE buyers. This indicates that capital cost support, through grants or tax reductions may be useful.

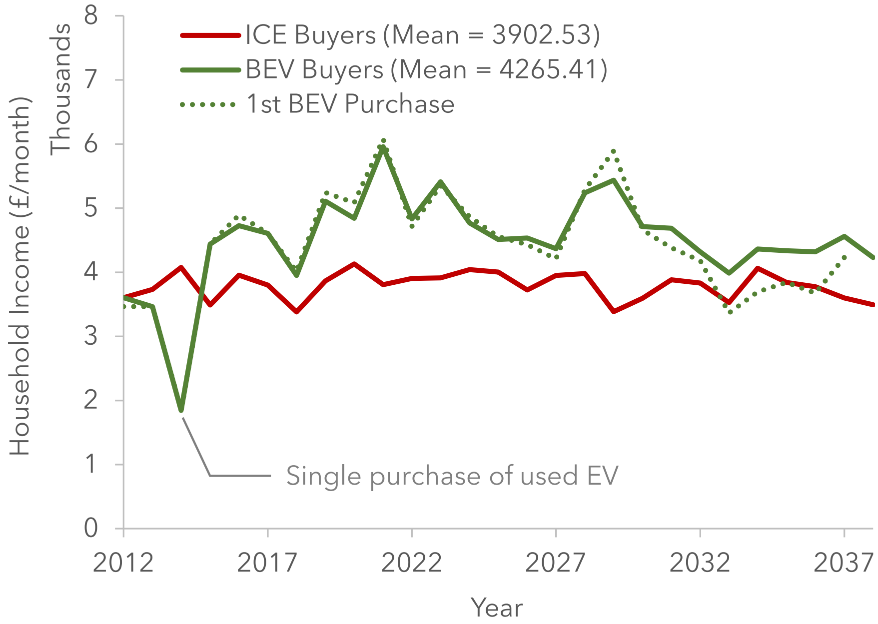


Figure 4.6: Mean household income of of BEV buyers and conventional ICE buyers over time.

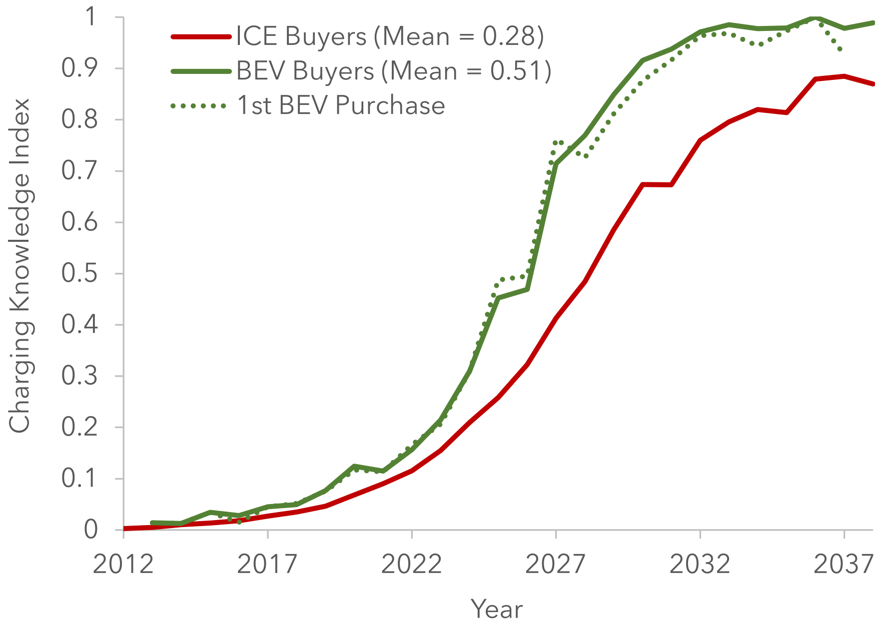


Figure 4.7: Mean charging knowledge (index) of BEV buyers and ICE buyers overtime, showing BEV buyers have a greater knowledge of charging environment.

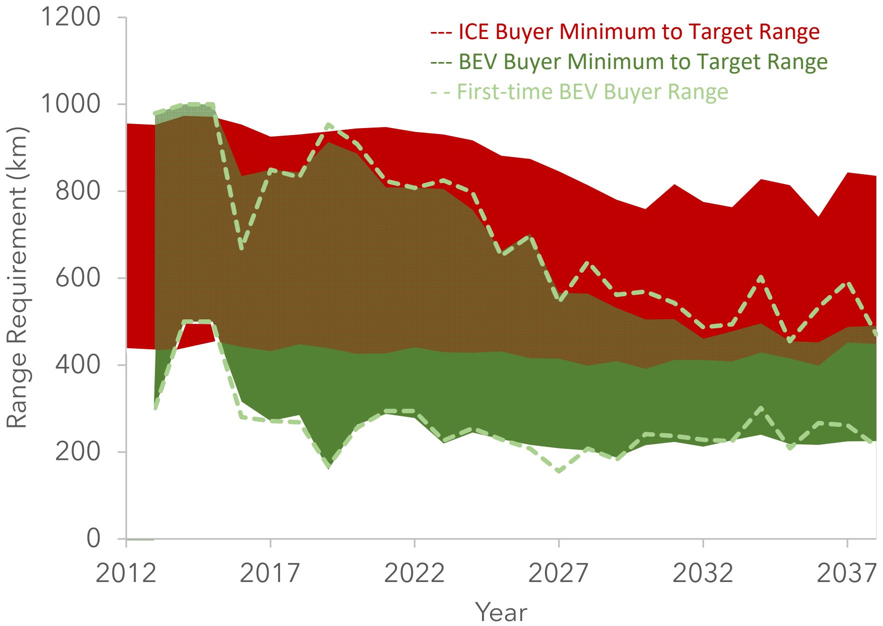


Figure 4.8: Mean minimum to target range requirement of ICE and BEV buyers, together with first-time BEV buyers, showing BEV buyers prepared to accept lower ranges, but desired range beginning to converge over time.

4.4.3 Buyer charging knowledge

Figure 4.7 illustrates the impact of charging knowledge acquisition on BEV uptake, showing that BEV buyers have a greater knowledge. This translates into driver range requirements which influence acceptable range during the car selection process. Figure 4.8 compares the minimum and preferred (target) range for BEV and ICE buyers illustrating that whilst desired ranges are similar initially, over time, BEV buyers become comfortable with lower range vehicles. Similarly the range requirement of ICE buyers also reduces as the mean number of BEV-owning peers increases, resulting in a modified range attitude. Note that first time BEV buyers will generally have slightly lower charging knowledge than repeat purchasers and this is indicated in their slightly higher target preference in later years. This approach to modelling car owner knowledge and range desires provides some insight into acceptable vehicle range, suggesting that, combined with appropriate levels of infrastructure, range desires may converge to a mean of around 500km. Whilst this is substantially less than a typical ICE car, it is greater than the average BEV car at the time of writing.

These insights indicate the need for a clear communications strategy from Governments and industry highlighting the availability of charging infrastructure, par-

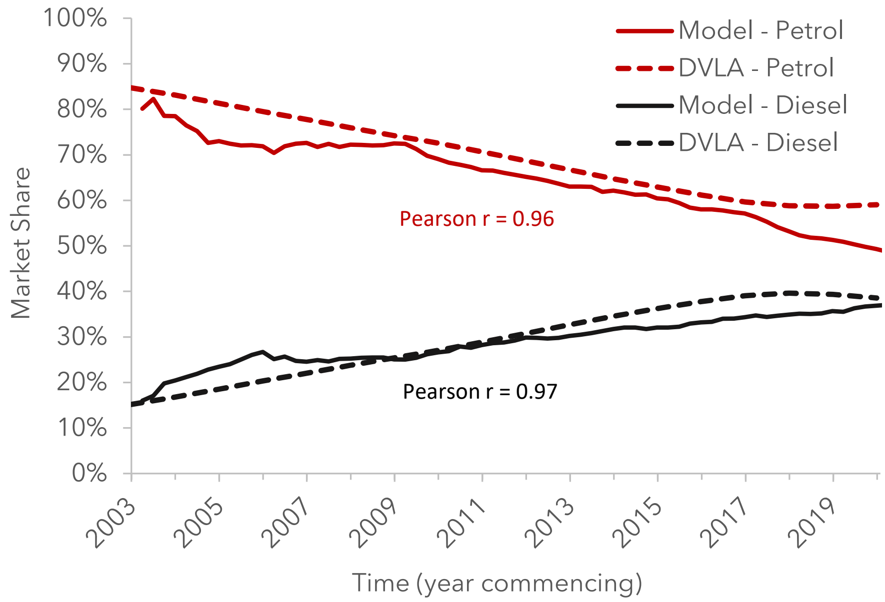


Figure 4.9: Comparison of DVLA [226] fleet fuel type data with modelled outcomes showing good match, but poorer in later years due to over estimate of shift to AFVs

ticularly on major routes where the majority of journey-critical rapid charging activity is likely to occur. The initial range requirements in the model are a function of surveyed non-stop driving time preferences in the UK[183], which also suggests greater emphasis on safe driving periods (2-3 hours continuous driving) and more attractive locations to break journeys for charging would contribute usefully to reducing desired vehicle ranges.

4.5 Fuel modal shift hindcast

Adoption of AFVs is still in its early days, with insufficient data to assess the accuracy of the model for large scale changes in drive train. Thus to provide confidence, a comparison of the historic mix of petrol and diesel vehicles in the UK fleet is made here. Figure 4.9 shows that the model can accurately reflect the shift from petrol to diesel during the 2000's. There is no attempt to model the 'Diesel-Gate' scandal [22], which led to a rapid slow-down in the sale of diesel cars from 2015, but changes to fuel-based tax regimes are included. From 2017 the model error for petrol vehicles increases and this can be traced to an overestimate of the shift to AFVs.

4.6 Brand and segment loyalty impacts

The set of cars used in the simulation include only a limited selection from each vehicle segment, typically just one of each power train, although different battery size models are included. This simplification means that brand does not influence purchasing decision. To overcome this, brand loyalty is simulated by including a probability that any given car within the car owner agent's purchase pool is available in a specified brand. Figure 4.10 illustrates the proportion of vehicle manufacturers offering each of the three types of AFV modelled between 2014 and 2018 and a Bass Diffusion Curve fitted on the assumption that 80% of vehicle manufacturers will be offering AFVs in all their segments by 2025 and all manufacturers will be doing so by 2035, the date at which the UK Government is currently indicating a potential ban on the sale of fossil-fuelled cars. The data points, based on analysis of DVLA statistics [226], illustrate the low-level availability (at 2018) of brands offering EVs. The curve presented could be seen as a function effectively imposed by Government policy.

Car owners were assigned brand and/or segment loyal with a probability of 0.2 and 0.4 respectively. At each purchase decision the assignment was re-evaluated with a probability of 0.05; i.e. car owners could change from being loyal to non-loyal during the simulation, but only with a low probability. At the time of a purchase decision, segment loyalty was modelled by making a car a valid purchase option only if the car owner was not segment loyal or the car was of the same segment as their existing car. Car owners making distress purchases (due to scrapping of their car (Section 3.9.4) or budget constraints (Section 3.7.1)) were allowed to move segment, but those with children were still prohibited from purchasing the smallest class of car. In respect of brand loyalty, a car was considered a valid option if:

- the car owner was not brand loyal
- it was the same model as the owners existing car
- it was a petrol or diesel car (on the basis all manufacturers produce such cars)
- with a probability given by Figure 4.10 if the car owner was brand loyal

HEVs are ideal to investigate brand loyalty, since the Toyota Prius was available in the UK market from 2000 but, as illustrated in Figure 4.10, other brands did not emerge until around 2014. In Figure 4.11, the modelled HEV adoption curve with and without brand loyalty is presented, together with the actual UK market share,

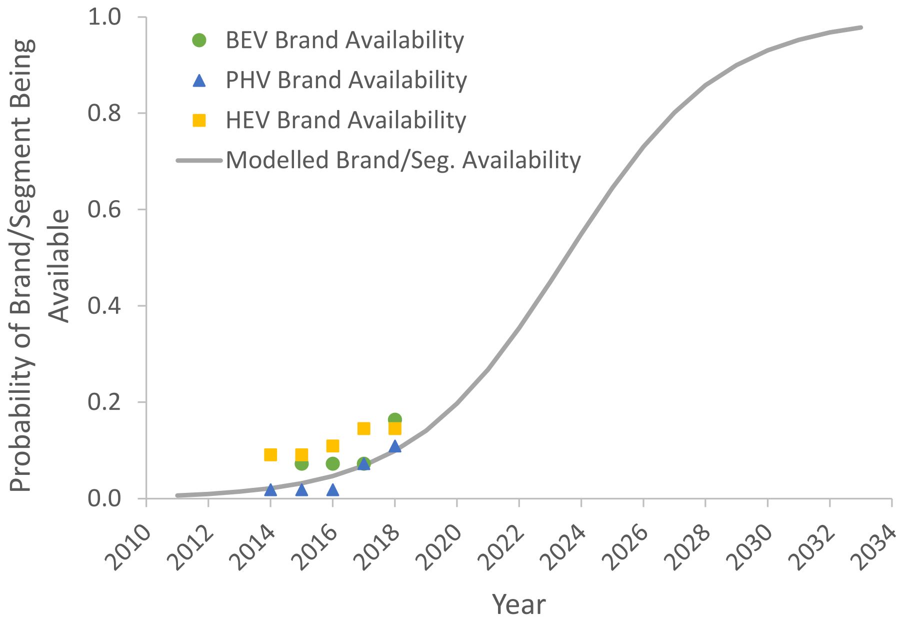


Figure 4.10: Chart shows the modelled probability that any given car selected by the car owner as a possible option is of the segment and brand desired (grey solid line). Data points represent the probability of a brand offering a specific type of AFV based on UK DVLA Statistics (2014-2018).

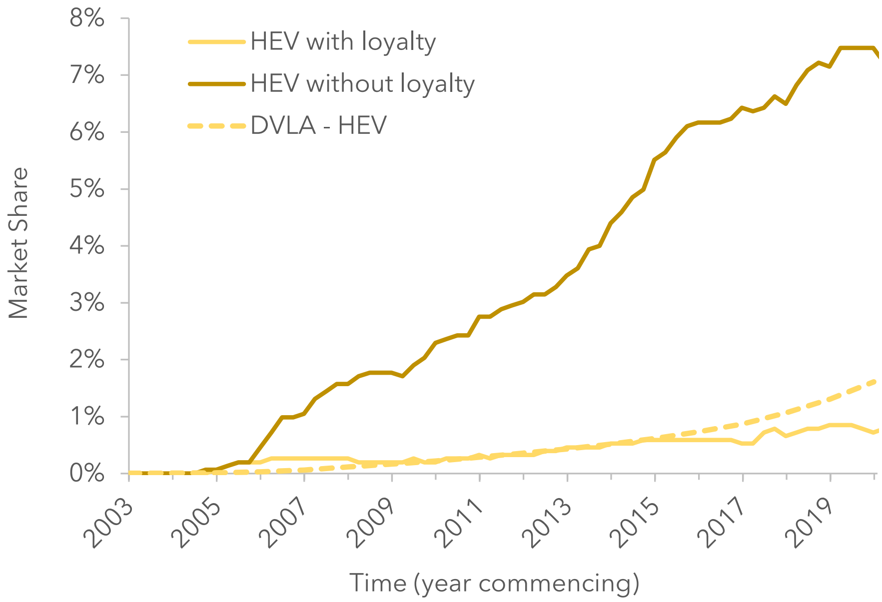


Figure 4.11: Comparison of DVLA [226] HEV market share data with modelled outcome showing the effects of brand availability. (Note beyond 2020, HEV market share climbs to 2% by 2024, flattens and then declines from 2026)

showing that the addition of the loyalty function has a significant impact on early adoption of HEVs bringing the market share much closer to historic data. In more recent years, the HEV market share is under-forecast, this may be a combination of HEVs being more widely available than the average AFV S-curve used (yellow squares, Figure 4.10) and an overestimate of BEV sales.

Figure 4.12 presents the modelled forecast of EV adoption with and without brand loyalty from 2010 through to 2038. This illustrates how brand loyalty has a significant impact on adoption up to the point in 2030 when a lack of vehicles with acceptable range and cost flattens the curve. In this base simulation only cars available as of 2020 are included. This means the longest range BEV is a Tesla Model S at 542km and a launch cost of £93,000; the highest range car at a more practical price point is the Kia e-Niro with a range of 480km at a launch cost of £35,000. The effect of this (Figure 4.12) is that the adoption of PHVs , with a range similar to ICE vehicles, continues to accelerate whilst BEVs remain flat. In mid 2030, the impact of brand loyalty is approximately 6 percentage points, which would equate to ca. 2 million vehicles across the UK. Thus brand loyalty can be a significant factor in adoption. Figure 4.12 (inset) also shows that the model over-estimates the adoption of BEVs in early years. It is, however, reasonably accurate

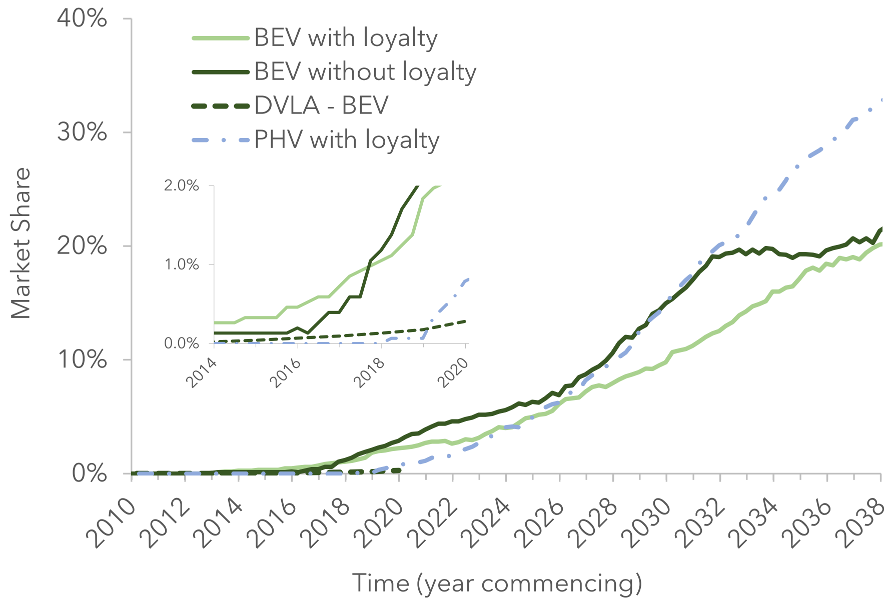


Figure 4.12: Forecast of BEV market share showing the effects of brand availability. PHV market share included to illustrate impact of lack of range on adoption post 2030

for both HEVs and PHVs. This may be the result of additional *Status Quo* bias [35, 132] since BEVs represent a bigger step away from conventional ICE than to HEVs or PHVs.

Figure 4.13 sets out the BEV ownership models, without ICE parity, over the 20 year period (the maximum modelled car lifetime) from 2013 to 2033 when the curve has flattened. In this figure, all new company and personal leases are new cars, whilst loans and purchases can be new or used. Company leases of BEVs begin from 2020 when the tax benefits are substantially improved. Commencing from 2023, there is a greater proportion of direct purchases, reflecting the availability of depreciated fleet cars arriving in the market. Tax benefits on fleet BEVs assist in two ways; firstly, they provide a lower cost entry point for BEV buyers and secondly car owners are more likely to have communication with a BEV owner thus allowing adoption of BEVs by more imitators in the simulation.

4.6.1 Segment switching

The simulation includes cars of different segments in order to reflect both segment loyalty and car owner aspiration, whilst this may not be critical to the target outputs, it will have some impact on battery sizing in BEVs and adoption where there

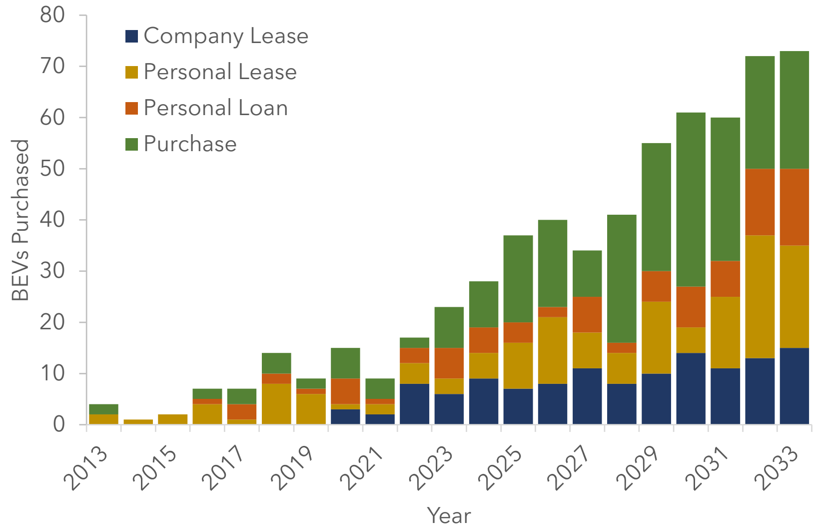


Figure 4.13: BEV ownership types over 20 years from 2013. Includes new and used car purchases and shows company leases becoming significant from changes in tax benefits in 2020.

is a lack of power-train availability in a given segment.

Figure 4.14 illustrates how drivers adopt different segments over the trial period. The aspirational component of vehicle selection, combined with advertising of new models, does pick up the switch to SUVs effectively. DVLA statistics [226] show that 'dual purpose' or SUV (these names are used interchangeably in the industry) segment vehicle sales rose from 248,000 per year in 2013 to 562,360 in 2019. Over the same period, the supermini class sales declined from 813,000 to 686,000 per year. However, the simulation also forecasts a significant switch to the smallest segment of car, which also appears to be at the expense of the supermini; this did not happen in practice. This is a result of the aspiration index over-valuing new cars against larger cars and the timing of new model introductions (and hence greater advertising). In practice it was not possible to arrive at a set of parameters that both fully replicated the shift to SUVs and maintained other segments at levels consistent with observed numbers. Since the presence of large numbers of very small vehicles would have a greater impact on battery sizing and vehicle efficiency, the analysis presented in the results section is based on a set of parameters that maintained more status quo over the period. This is shown in Figure 4.15. This has a broadly similar mix of vehicles to those actually present in

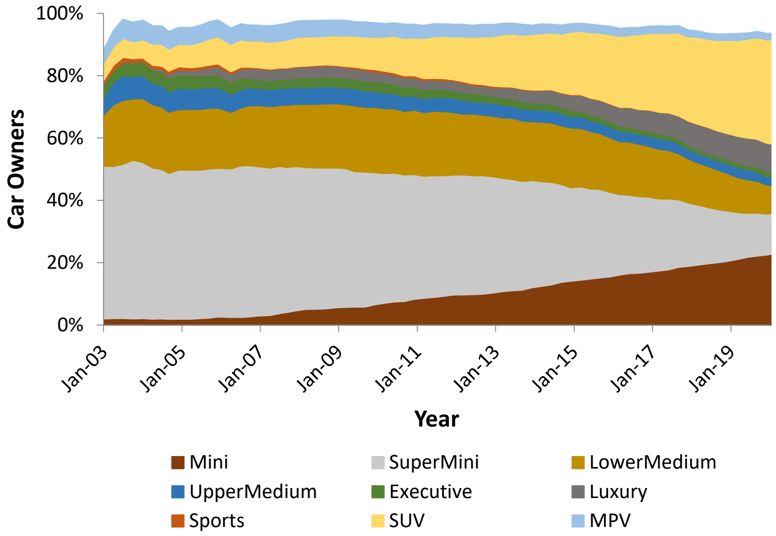


Figure 4.14: Car segment ownership profile from 2003 to 2020

2020. The shift to sports vehicles from the 2030's is driven by driver aspirations and having access to more funds due to the lower operational costs of EVs.

4.7 New car generation and depreciation functions

Figure 4.16 compares the car generation and depreciation functions with the unmodified vehicle and pricing (Figure 4.12) and a simple 2025 range and price ICE-parity case. In this scenario, a BEV car becomes available in each segment at the average cost of a petrol vehicle in that segment and with a 50kWh battery for segment 1 and 2 (super mini and mini) and a 100kWh battery for all other segments. A 10% improvement on the current best-in-segment efficiency is also assumed giving a range of between 347km (for a mini) to 825km for the best performing vehicle. Here the uptake of BEVs, where the simulation generates new models based on Bloomberg costs, is somewhat accelerated from 2023 compared to the base case due to lower cost EVs becoming available earlier. However, after 2028, the ICE-parity case shows greater growth as a result of fewer rejections by range-rhetorical drivers.

Modified depreciation rates have little affect on the outcomes here. However, there is a slight increase in uptake from 2026 to 2030 when depreciation effects are included which may be a result of lower range BEVs depreciating more

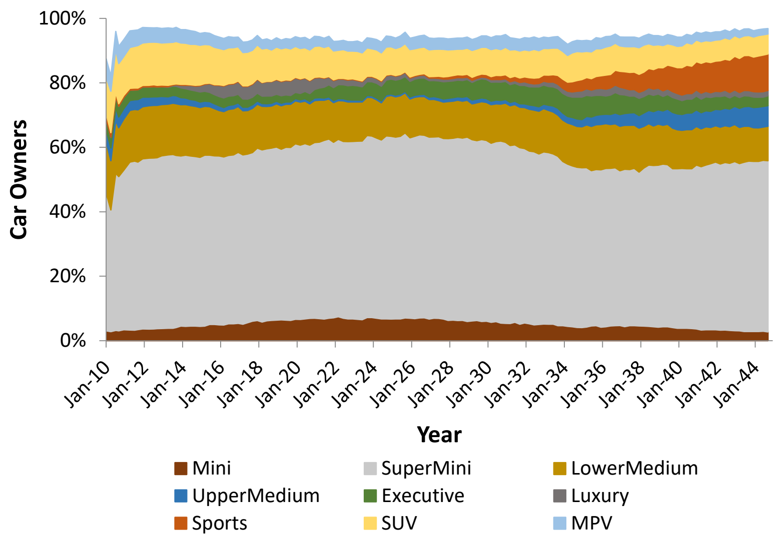


Figure 4.15: Car segment ownership profile from 2010 to 2044 as employed in postulated policy and grid analysis.

rapidly than longer range cars and thus becoming more affordable. After 2030 this switches over, suggesting that consumers are, to a limited extent, beginning to seek out BEVs. This simulation includes a ban on ICE vehicle sales in 2040 and there is some further divergence here, suggesting ICE vehicles are depreciating more rapidly than BEVs making them a more attractive option for some buyers.

4.8 Realistic forecasting of electricity demands

A key objective of the model is to generate realistic charging demand profiles. Figure 4.17 compares the modelled household charging profiles (with half hourly profile averaged to hourly) in 2019 and 2035 to real world averages from a 2019 NGC sponsored project which collected data on 8 million charging events [156]. The model produces a more volatile profile due to the small number of vehicles (43 in 2019) and what is effectively a single week of charging and therefore no averaging over individuals' journey return times. For the purposes of comparison, an immediate 'charge on return home' strategy is assumed, which will not be adopted by all car owners in the NGC data. Despite this, the model forecasts some of the key features identified by NGC; notably that the charging peak occurs slightly later than the system peak demand, with some overlap, and weekend

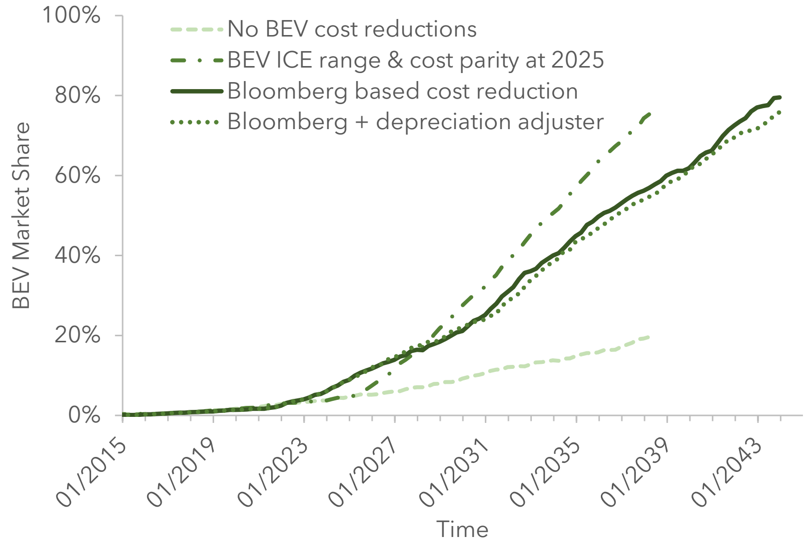


Figure 4.16: BEV market share with Bloomberg-based car cost reductions with and without depreciation effects compared (2040 ICE sales ban included) to no cost reductions and full ICE parity from [133]

charging produces a flatter profile. A 2035 profile is included here to illustrate the situation with more cars and therefore more smoothing, which delivers a better fit to the NGC data. Spikes in the modelled data can be caused by returns from unplanned trips.

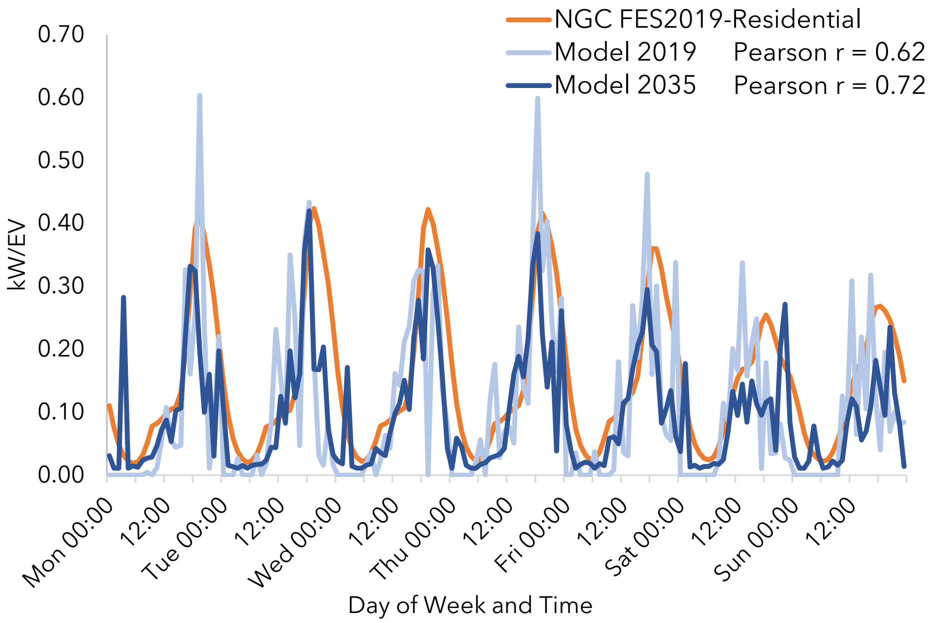


Figure 4.17: Comparison of modelled and actual charging profiles on a kW per EV basis. Model has 43 EVs in 2019 and 316 in 2035. Actual profiles collected as part of NGC project [156].(Two outlying data points from 2019 data removed for clarity - caused due to small number of cars)

Chapter 5

Methodology: Renewables and Electric Vehicle Public Transport Integration model

This chapter sets out the methodology employed in the REVIT model. The first section provides a brief summary to enable the reader to obtain an overview of how the model is assembled. This is followed by detailed descriptions of the data sets and their application, algorithms and other functionality grouped by agent type as illustrated in Figure 5.1.

5.1 REVIT model overview

The objective of the REVIT model, which employs agent-based simulation within Anylogic, is to evaluate the costs and benefits of a bi-directional bus PnR facility (or hub) which incorporates wind and solar generation, energy storage and electric vehicle charging for PnR users. The hub is considered bi-directional since it provides a facility for commuters travelling to work during weekdays, but also for tourists visiting local attractions, primarily at weekends. Figure 5.1 illustrates the main features and structure of the model. Wind and solar generation feed into a local network that supplies a bus depot with overnight charging facilities and the PnR site, which incorporates EV fast chargers (7.4kW) and bus rapid chargers (rated according to bus requirements). An onsite hub battery is incorporated whenever electric buses are used and an electrolyser when hydrogen buses are used; chargers and hydrogen dispensers are also added accordingly. The primary purpose of the energy storage is to maximise the self-sufficiency of bus operations from the hub, thus onsite battery charging and hydrogen manufacture are prioritised when renewable generation exceeds bus charging demand. Battery charging and hydrogen production also operate during off-peak hours when storage is low, and hydrogen production may also operate at peak times when even lower levels of hydrogen stock occur. Renewable generation output is updated at half hourly intervals, whilst charging activity (both bus and hub battery) is event driven or updated at 1 minute intervals to ensure that shorter duration rapid charge events and changes in EV charging demands are more accurately represented.

The buses may be electric, hydrogen or a combination of the two; the bus requirements are determined by the simulation based on initial preferences and the availability of buses with adequate range during the course of the simulation. For electric buses the charging strategy mixes overnight depot-based charging and opportunity charging between route departures, either at the hub or at the route end point, where available, prior to a return journey. Hydrogen buses refuel on return to the depot at night. Bus routes are generated by the modelling software routing algorithm based on a series of bus stops with latitude and longitude data. The route distance is used to estimate energy consumption with an adjustment for ambient temperature.

EVs arrive at the hub based on a predefined schedule and with a randomly distributed charging need. Each driver also has a predefined price threshold based on the expected distribution of alternative home-based or public charging tariffs. An algorithm charges vehicles according to their price threshold and the availability of excess renewable generation.

The power generation, consumption, battery use, hydrogen production, self-sufficiency ratio and various bus operational data is calculated at half hourly intervals. A rolling Net Present Value (NPV) calculation determines the NPV at the end of each month, taking into account the depreciated value of the assets, and summary data is presented annually.

The model does not include driver costs or passenger revenues. The objective is to understand how a hub would integrate with EV use and renewables and compare hydrogen and electric bus options, since the routes remain the same, these elements would also be the same and thus the calculated NPV is representative of the relative merits of each scenario considered.

In the following sections, the input data requirements are presented with a discussion on their application in the simulation. This is followed by sections covering the functionality of the agents within the model that align broadly with the the boxes in Figure 5.1.

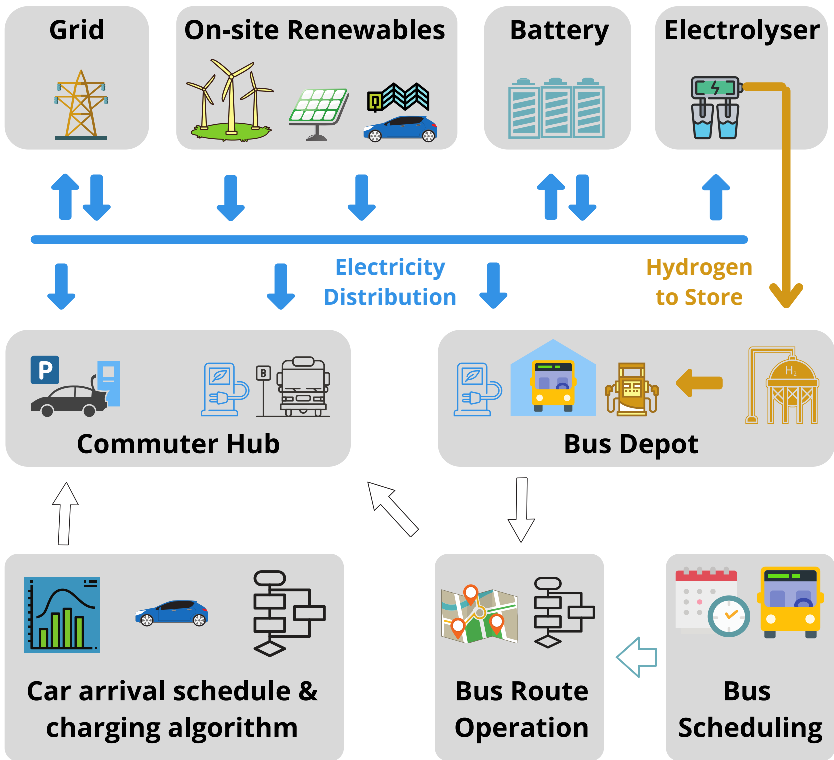


Figure 5.1: Overview of the REVIT model showing main features of the commuter hub and functionality of car and bus agents.

5.2 Bus stops and routing

5.2.1 Bus stops

Bus stops are defined with a set of parameters as follows:

- Unique ID
- Name
- Latitude and longitude
- Private wire
- Bus overnight chargers (depot only)
- Bus rapid chargers (used by hub and destination stops only)
- Hydrogen refilling points (depot only)
- Parking spaces (hub only)
- Car chargers (hub only)

Private Wire Specifies whether this stop exists within a private wire network connected to the hub generation. This allows a stop (such as the bus depot itself) to be in a different place to the hub, but connected to the generation sources by 'private wire' such that all power flows can be considered 'behind the meter'. Electricity consumed within the private wire network is assumed to have zero cost in the NPV calculation (plant capital and maintenance costs are included).

Bus overnight chargers Defines the minimum number of chargers at the depot (for CAPEX purposes). The base simulation adds further chargers, when required, to ensure a charger is available for every bus. Depot chargers may have a different charging rate (kW) to bus rapid chargers depending on the bus types specified.

Bus rapid chargers Defines the number of chargers; the simulation adopts the charging power specified for the bus type.

Hydrogen refilling points Defines the number of hydrogen fuelling points, for CAPEX purposes only; the simulation assumes that buses can always be filled on return to the depot.

Parking spaces Defines the number of parking spaces at the hub and is used in combination with a solar capacity per space to determine the peak output of 'solar carports' located above parking spaces.

Car chargers Specifies the number of parking spaces that include an EV charger. Cars arriving at the hub with a charging requirement above a specified threshold will choose a charging space when when available.

5.2.2 Bus routes

Bus routes are defined with the following parameters:

- Route number
- Route name
- Monday-Friday start time and end time
- Saturday start-time and end time
- Sunday start time and end time
- Average speed
- Service frequency
- Minimum dwell time at destination
- Route reversal
- Stop sequence

Consideration was also given to including a parameter to adjust the bus efficiency based on the route, however, following discussion with 'Caetano Bus' (a Portuguese bus manufacturer with a UK arm [210]) it was decided that deriving a suitable figure was unlikely to be possible without route trial runs.

Start and end times The start and end times define when a route first starts and the time after which there will be no further departures for the given day of the week. The simulation does not incorporate schedule variations for public holidays since these would be unlikely to have significant impact on the self-sufficiency or financial outcomes.

Average speed Defines the average speed on the route and is used to determine the route duration. A further 1 minute is added for each stop to allow for deceleration, acceleration and passenger boarding time (t_r in Equation 5.1).

Service frequency Specifies the interval between departures from the first stop in the route, regardless of whether the previous service departure has completed the route.

Minimum dwell time Defines the minimum time that a bus must remain at its destination before commencing a return journey or starting a new route. This provides an allowance for delays (which are not simulated) and, by setting this to 15 minutes or more, electric buses may make use of rapid charging facilities at the destination.

Route reversal Defines whether the route is reversed once the destination is reached.

The return departure time of services where the route is reversed from the destination is established from Equation 5.1, such that the return leg will start on the next highest multiple of the minimum dwell time after the initial departure. (i.e. a service departing at 07:30 with a minimum dwell time of 15 minutes, which takes 52 minutes to complete the route would have a cycle time of 1 hour 15 minutes, starting the return journey at 08:45).

$$t_c = t_{dmin} \times \left\lceil \frac{(t_r + t_{dmin})}{t_{dmin}} \right\rceil \tag{5.1}$$

where:

t_c	the total cycle time (initial departure to return departure) in minutes
t_r	time taken to complete route in minutes
t_{dmin}	the minimum dwell time in minutes

This approach enables the model to run without the timetable creator being aware of the time taken to complete each route.

Stop sequence For each route, a sequence of bus stops is also specified. The simulation automatically routes buses by the fastest available route between stops, at the average speed defined, using Anylogic's routing server.

5.3 Bus characteristics

Buses are defined by the following parameters:

- Bus type (unique identifier)
- Bus fuel (hydrogen or electric)
- Number at start-up
- Battery energy rating (kWh)
- Electric bus efficiency (km kWh^{-1})
- Electric bus depot charge rate (kW)
- Electric bus depot charge efficiency
- Electric bus rapid charge rate (kW)
- Electric bus rapid charge efficiency
- Hydrogen bus tank capacity (kg H_2)
- Hydrogen bus efficiency (km kgH_2^{-1})
- CAPEX (£)
- Maintenance cost (£ km^{-1})
- Major service cost (£)

Number at start-up Sets the number of each type of bus at the start of the simulation. The model generates additional buses as needed to complete the specified schedule. These additional buses are created based on the preferred type specified in the simulation start-up. This allows the simulation to start with, for example, a fixed number of hydrogen buses and for any additional buses to be based on an electric model.

Battery energy rating Defines the capacity of the battery when new. Battery degradation is assumed to be linear with cycles. Since the batteries undergo deep cycling on an almost daily basis, it is assumed that cycle ageing will dominate over calendar aging. The method applied is describe in Section 5.6.

Electric bus efficiency Defines the average operating efficiency of the bus at 23°C (WLTP standard test temperature; no standard currently exists for electric bus performance).

Charge rates and efficiencies Define the charging speed (kW) and efficiency for overnight charging, which may be slower AC charging via an onboard charger, and daytime rapid charging from a DC charger. Some buses use DC charging for both.

Hydrogen tank capacity and efficiency Define the tank capacity in kilograms of hydrogen and the efficiency; no allowance is made for stack degradation as discussed below.

CAPEX Sets out the capital cost of the bus; no inflation or cost reductions are incorporated in the model for later additions to the fleet. This is not of significance for hydrogen buses since there is no range degradation (see below) and all the buses required for the lifetime simulation are present by the end of the first week of schedule. Electric buses may be added later in the simulation, due to battery degradation, and thus this simplification may have some effect on the financial outcomes.

Maintenance cost Defines the variable maintenance cost per km travelled. It excludes the major service costs corresponding to battery or fuel cell stack replacement.

Major service cost The major service cost is the cost of a battery replacement for the electric bus and a stack replacement for a hydrogen bus.

Performance degradation

Caetano (a European bus manufacturer using Toyota fuel cells and selling into the UK market [210]) indicated that they expect a stack life of 30,000 hours, which to all intents and purposes means that the fuel cell lasts the life of the bus (nominally 12 years), since this is a utilisation of about 30%, significantly higher than that achieved in the simulation. Stack aging results in reduced fuel cell efficiency, but with rates for hydrogen estimated at 2-10 μ Vh^{-1} [127], this would appear to have little impact on performance at 30,000 hours.

Caetano envisage replacing electric bus batteries at 70% SoH and note that this typically occurs at about 6 years of use; they also expect the battery cost to have declined significantly in this time; the model currently assumes a fixed cost as specified in the table.

The point at which a major service of either bus type occurs is included as a parameter that can be adjusted at start-up, since they represent a potential optimisation parameter; i.e. there is a trade-off between replacing batteries earlier or potentially needing to purchase a new bus.

5.4 Route agents

An agent is created for each route in the simulation. On start-up, each route agent calculates the length and duration of the route using Anylogic's built-in GIS router and the average speed defined in the route data. An event is also scheduled to run at the start of each day to determine the time of the first departure, if scheduled for that day of the week. A required depot departure time is calculated based on an assumed 40km h^{-1} speed to arrive at the initial stop 5 minutes prior to the scheduled departure time. This function also determines the total route-km for the route during that day; this is used by the scheduling agent to determine when buses can start returning to the depot (see Section 5.5).

When a bus is assigned to the route by the scheduling agent, a function sets the time of the next scheduled departure and decrements the route-km remaining by one route cycle. A copy of the route agent is then sent to the assigned bus, which uses it to determine the route stops.

5.5 Scheduling agent

The scheduling agent is responsible for scheduling buses on routes and also requests the creation of new buses when these are required. A scheduling window, here defined as 15 minutes, looks at all departures within the next 15 minute period and schedules appropriate buses. This operation occurs at intervals of half of the scheduling window; that period must be sufficient for buses to get from the depot to the start of any defined route. The function used to select a bus is illustrated in the flowchart Figure 5.2. The initial filter looks for buses with a 'next scheduled departure' within the scheduling window. Since the route's 'next scheduled departure' parameter is updated each time a bus is scheduled, only unscheduled departures will be included even if the window overlaps an already scheduled departure time. Rather than specify a minimum SoC as some models employ [119], a minimum percentage margin is added to the journey length when choosing a suitable bus; a value of 25% was chosen since this represents sufficient margin to enable journey completion in cold weather conditions (see Section 5.6). The route length will include the return journey when when route reversal is specified.

The initial bus filtering process removes buses that are already scheduled for a future route, though not those already on a route provided that they can complete the current route and reach the starting point in time (assuming a speed of 40kmh^{-1} from their final destination and an additional 'route changeover' time of 5 minutes). Buses at the depot can always be scheduled for a route provided they have adequate range.

The final bus selection is based on one of the following selection criteria for each simulation run:

- bus closest to the route start point
- closest bus unless all at depot, in which case bus with lowest mileage
- bus with lowest current mileage
- bus with longest current range
- a random bus

The effects of these options are discussed in Section 6.2.3.

If no suitable bus is available, then a new bus of the preferred type specified for the simulation is created at the depot; newly created buses are fully charged or have a full tank of hydrogen. On bus creation, the relevant capital costs are updated and, in the case of an electric bus, a new depot charger is added such that electric buses have a dedicated depot charger for overnight charging. If there were no buses available with adequate range (i.e. sufficient charge/hydrogen fill), then the new bus is logged as being required to overcome range issues. Note that hydrogen buses are assumed to be filled once per day and so there may be theoretical cases where a hydrogen bus could be refilled to enable a route to be completed, but in practice, due to their long range, this does not occur in the case study here (i.e. run with only hydrogen buses, range additions are zero).

When a bus has been selected, a copy of the route agent is sent to it to provide route data. A copy is also returned to the originating route agent and on receipt, the route agent updates the next scheduled departure time and reduces the route-km remaining for the day by one route length.

Prior to completing the scheduler function, the sum of all remaining route-km for the day is calculated. If the range remaining in buses currently at the end of a route (either pending a schedule or rapid-charging), then a flag to indicate depot

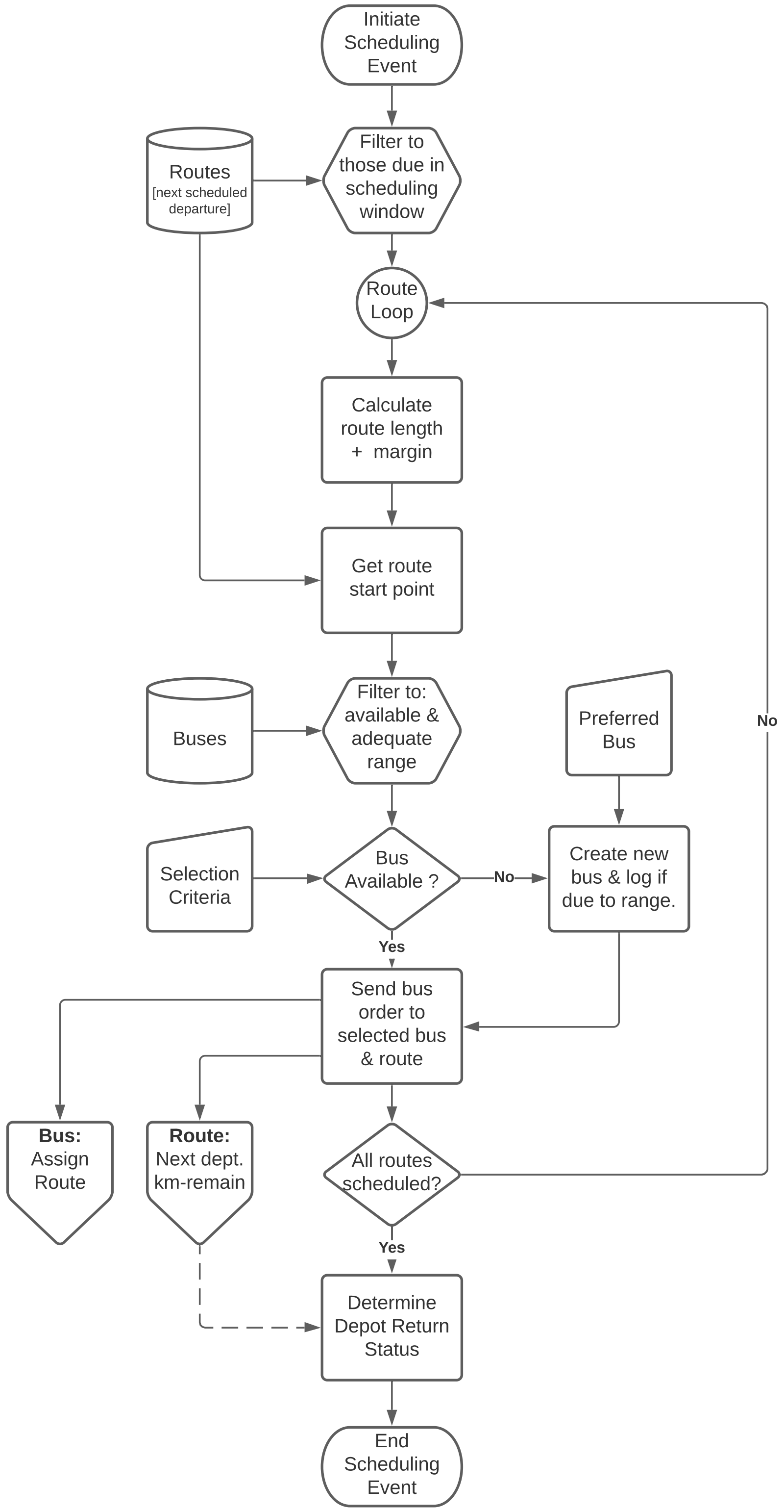


Figure 5.2: Bus selection flow chart, showing main steps in scheduling buses

returns can commence is set and, thereafter, buses completing their route at the hub will return to the depot rather than wait for a new schedule. This allows depot charging to commence before off-peak hours when renewable generation exceeds demand (see Section 5.8).

5.6 Bus agents

The same agent type is used for both electric and hydrogen buses, with different functions selected for fueling/energy use; in principle, this allows the same model to be employed for hybrid buses, though this is not fully implemented in the current version. Thus a hydrogen bus, which normally includes a battery, is currently assumed to require only hydrogen fuel and is not rechargeable from mains supplies.

Figure 5.3 sets out the main bus states and operational flow. When buses are created, the capital cost for that bus type is added to the total costs and, in the case of electric buses, an additional depot charger is also added, if required, with associated costs.

When a bus arrives at the depot, any previously scheduled routes and timings are reset to null. If the bus is a hydrogen bus and the tank is not full, then it will be immediately sent to the refill station (note there is no queuing for the hydrogen filling facility) and then returns to the 'At bus depot' state after 10 minutes. For electric buses, the current SoC must be less than 98% and it must be either an off-peak period or there must be sufficient export from the private wire network to meet the full charging demand of the bus. The number of available chargers is also tested, although in the simulation here, there are always sufficient chargers for the number of buses. The bus will return to the 'At bus depot' state when the SoC exceeds 99%. The charge rate is fixed throughout the charge and added to the depot demand and at the end of each trading period, the total kWh charged are accumulated.

If the scheduling agent requests the bus for a route, then it will change state to 'Move to start', regardless of whether it is currently charging or not; i.e. provided it has sufficient range for the route, as calculated at the end of each trading period, then it is deemed available for service. The bus is moved to the start-point by the fastest available GIS route at a speed of 40km h^{-1}. The bus then waits at the start of the route until the scheduled departure time.

After the scheduled departure, the bus cycles through each stop being routed by the fastest available route at the route mean speed. As it arrives at each stop, the SoC and current range are adjusted based on the bus efficiency, segment length

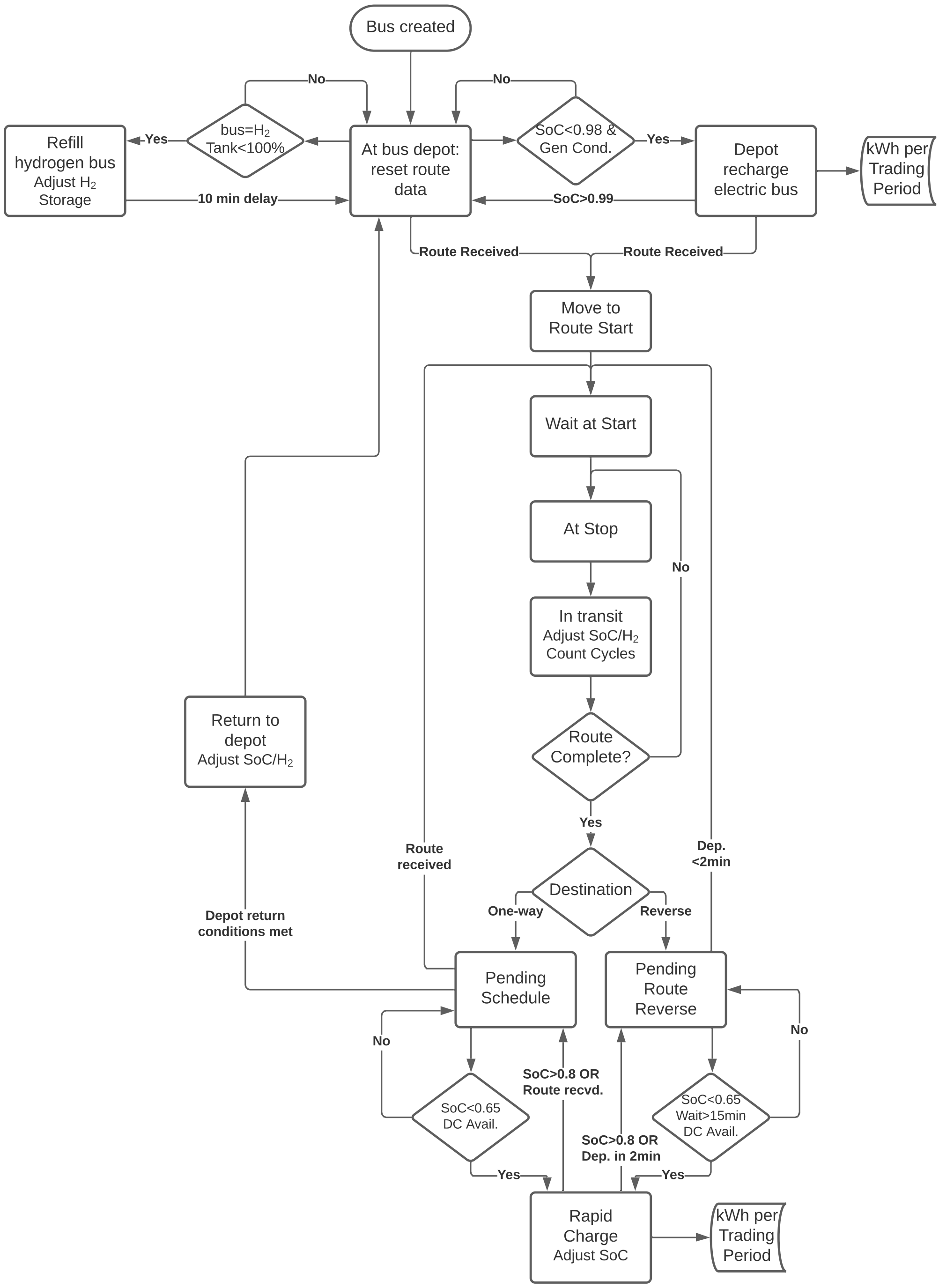


Figure 5.3: Bus operation state chart

and estimated ambient temperature. The temperature adjustment uses daily minimum and maximum temperatures sourced from Stark [203]. For simplicity and speed of processing the daily minimum is assumed to occur at 06:00 and the maximum at 15:00 with temperatures linearly interpolated. Whilst this does not represent an accurate temperature profile, it does ensure that the temperatures experienced over the year are representative of real world conditions. There are two principle means of adjusting electric bus performance with ambient temperature;

- calculate the energy requirements based on the standard vehicle power calculation (DIN70030)
- use manufacturer's performance data with a temperature adjustment factor.

The former approach suffers from generating only the power requirement at the motor (or battery if a motor efficiency map is included), in practice, the performance of batteries also varies with operating temperature and consequently ambient conditions, though also influenced by the battery cooling system. The latter suffers from some uncertainty about manufacturer claims and specific operating conditions at the claimed efficiency since these are not subject to standardisation, there is also a lack of data specific to buses. Foley [90] indicates that for resistive heating, the total heat load can comprise 61% of electrical load on the coldest day of the year or around 30% for a heat pump system. Kunith et al. [129], provide some indicative calculations of auxiliary load for a 12m single deck bus as illustrated by the solid orange points in Figure 5.4. These can can be converted to a factor to apply to base efficiency by assuming constant speed operation, as illustrated by the orange dotted line (using a base efficiency of 0.75km/kWh). Figure 5.4 also plots performance vs temperature for some 6000 EV's (not buses) logged by Geotab, a private fleet management company [96]. This later data includes battery performance effects as well as heating/cooling demands and other auxiliary loads. The triangle point is the WLTP standard test temperature of 23°C. The chart shows that including all temperature effects produces a much more pronounced curve and with the lowest temperatures, indicates that energy consumption could more than double as suggested by Foley. Whilst the Geotab data may not be reflective of electric buses, it does appear to provide a more conservative approach than other strategies and using a lower base efficiency than quoted will also reduce the range over which performance is greater than stated. One might expect this to be the case for electric buses due to higher base auxiliary loads than in a car. For these reasons, the model adopts a base efficiency set to 95% of that quoted and applies the Geotab efficiency factor at any given ambient temperature; the modelled performance is shown in green in Figure 5.4. The efficiency of hydrogen

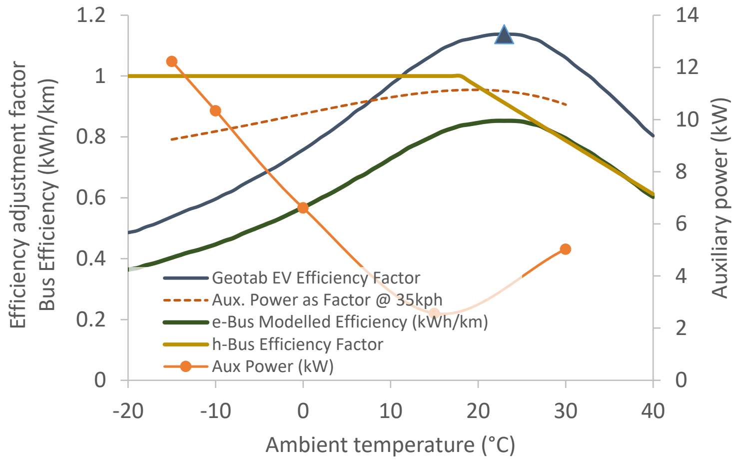


Figure 5.4: EV Range as fraction of WLTP range [96] and E-Bus auxiliary loads vs ambient temperature [129], together with as-modelled electric bus efficiency

buses is assumed to be constant below 18°C, since heating can be supplied from fuel cell waste heat. Above this point it is assumed that increasing amounts of air conditioning will be needed to maintain a bus temperature of circa 20°C due to both solar gain and the number of passengers. Foley [90] indicates up to 30% of energy use on the hottest day; the air conditioning load is assumed to increase linearly from 18 to 35°C, with a range performance reduced by 30% at 35°C.

On arrival at the destination, electric buses may connect to a rapid charger provided there is one available at the location (this includes a test to ensure chargers are not already in use by other buses) and the battery SoC is under 65%. In addition, there must be at least 15 minutes of waiting time at the destination for buses returning by the same route. This is to ensure adequate time for drivers to park-up, connect and disconnect since the buses require plugging in and do not have inductive or pantograph charging.

The charging calculation is event driven to capture short charging periods that may overlap half hourly trading periods; each time a bus commences a charge (whether at a destination or at the depot), the start and end times of the charge are logged, an event runs at the the end of each trading period to calculate the charge in that period and the change in SoC. The currently available bus range is calculated from the SoC and the ambient temperature. The total number of equivalent full-cycles (i.e. the proportion of total capacity charged) is also incremented on charging. The charging rate at the depot and remote facilities can be different;

i.e. depot charging can be slow AC charging whilst remote charging can be fast DC charging. The buses modelled in the case study do not have on-board chargers and so the depot charging is at the same rate as remote charging.

For buses on a reversing route, the bus stops charging 2 minutes prior to the scheduled return journey departure and waits at the start; the route stops are then cycled through in reverse order and the bus will complete the journey in the 'pending schedule' state and may then charge again if the charging conditions are met. At any time during the scheduled route, a second route may be sent to the bus pending completion of the current route. Since the scheduling algorithm ensures that the bus will have sufficient charge for the next route, a bus with a new route pre-assigned moves immediately to the route starting point and waits for the scheduled departure time.

The scheduling algorithm maintains a variable containing the total route-km remaining for the day. If the buses currently on routes or rapid charging have sufficient range to complete that day's schedule, then buses will be allowed to return to the depot. All buses return to the depot at a defined time after completion of the final route.

On reaching the depot, buses are refuelled or recharged as described earlier. The total battery cycle count and fuel cell operating hours are also evaluated. SoH is estimated according to the number of full-equivalent battery cycles at a degradation rate of 1.11×10^{-4} of initial capacity per cycle [91]. For hydrogen buses, no performance degradation is modelled, but stack replacement can be scheduled after a specified number of operating hours. Based on discussion with Caetano bus, this has been set at 30,000 hours, meaning stacks are not replaced in the normal life span.

There is no allowance for downtime of the bus during this maintenance or for breakdowns at other times. Since it is necessary for operators to hold spare buses, it is assumed that this would apply equally regardless of bus type used and will not significantly affect the overall economic analysis. In practice, assuming a pure hydrogen vs pure electric fleet, it is likely to render the hydrogen fleet slightly less economically attractive due to the greater capital cost of hydrogen buses compared to pure electric buses.

5.7 Hub car arrivals and charging

A schedule defines the rate at which cars arrive at the hub by hour of the day separately for weekdays and weekends (the case study example can be seen at Figure 6.3). Cars are also assigned a random parking time (PERT distribution of 2 hours minimum, 10 hours mode and 16 hours maximum). On arrival at the hub cars choose a space with charging provision if they require more than a specified threshold of charge that day (4kWh as default). If all charging spaces are used or the car does not require charging, then it will seek a standard (non-charging) space. Car drivers are divided into those without access to home charging (probability 0.4 [150]) and then to contract charging and standard charging (arbitrarily assigned probabilities of 0.2 and 0.4 respectively). Within these groups, a normal distribution is used to represent the range of possible tariffs, see Figure 5.5. Public charging rates are based on data from ZapMap [241] and include a mix of public AC chargers and DC rapid chargers. The 'Home Standard' rate assumes off-peak charging on a standard economy 7 type tariff and 'Home EV Contract' is indicative of more tailored EV tariffs. These were sourced from web-based supplier offers and quotes and include, for example, the Octopus Energy 'Agile' tariff which can see negative prices overnight. The charging cost assigned to the car is used as a threshold to determine when charging occurs. Each car is also assigned a desired charge in kWh using the PERT probability function illustrated in Figure 5.6. This is based on the principle that some owners will seek to charge everyday (the average commute being 10 miles each way, consuming ca. 5kWh in total), whilst others may wait until the car battery is nearly depleted to re-charge. Based on analysis from the BEVI model, batteries are likely to be of a capacity in the range 60-80kWh, and this has been used to form the limits of the probability function. The peak probability, 12kWh, is indicative of an average mileage driver recharging every 2 days. The minimum threshold is included since increasing this implies greater charger utilisation; i.e. if drivers know that they cannot plug in below a certain threshold (perhaps delivered through a penalty charge) then, on average, the kWh delivered will be higher and only those more in need will be able to plug in.

The charging tariff is varied each minute according to whether there is excess generation (i.e. the hub is currently exporting) and what the import tariff is. When exporting, the car charging tariff is the half-hour trading period export tariff plus 25% and when importing it is the import tariff plus 25%. At the start of each trading period, a 'charging stack', comprising all cars willing to pay the charging price extant at the time, is created. Those cars will enter, or remain, in the charging state for the entire 30 minute trading period. Every 5 minutes, the current tariff is evaluated by the car and it will either charge at full rate (7.4kW) if the tariff is below its threshold, or it will reduce the charge rate to the minimum allowable under the EV charging protocol (1.4kW) if above. This helps prevent 'chatter' as cars turn on and off and is a realistic strategy given the desire to reduce switching

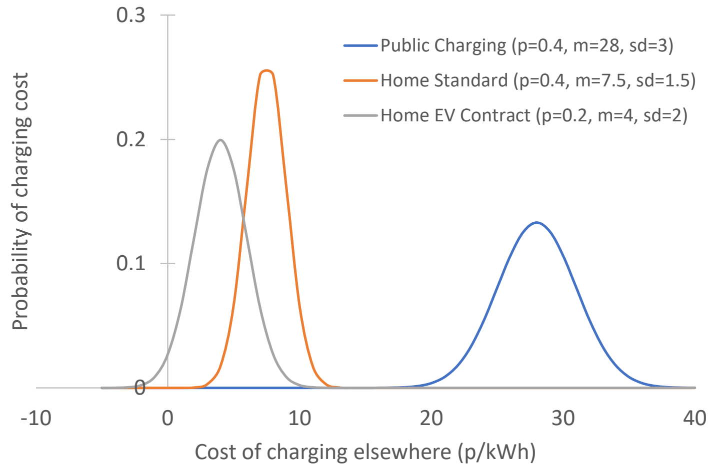


Figure 5.5: Cost of charging elsewhere for EV owners, used as charging cost threshold.

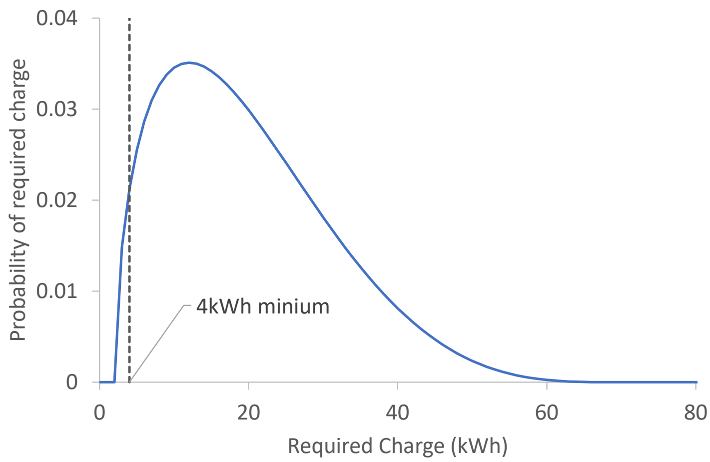


Figure 5.6: probability density function for volume of energy required by cars arriving at the hub. (PERT function with minimum = 2, mode = 12, maximum = 70)

and wear on relay contacts. In principle, such a scheme could be implemented in practice simply by having EV owners set a tariff threshold on the charger when they plug in; it does not necessitate communications with the car beyond that currently standard for AC charging. If a car accumulates its target charge, then it ceases charging, is removed from the stack, but continues to occupy the charging bay.

At the point of departure from the car park, the total amount paid for charging is credited to the private car EV charging total and the charger is released allowing the next car entering the car park to use it if required.

5.8 Generation agent

The generation agent is responsible for determining power flows within the hub. The flows are recalculated each minute to take account of fast charging demands which may exist for relatively short durations, however, wind generation data is only recalculated at half hourly intervals and solar is only available at hourly intervals. When electric buses are present in the model, a central battery storage device is added of a size specified during start-up, when hydrogen buses are present an electrolyser and hydrogen storage are added. The minimum storage size can also be based on the peak daily consumption. If this option is selected on model start-up, then the storage size will increase, adding to the CAPEX, during the first week of operation (since the schedule repeats each week) to the specified number of days storage if this is greater than the minimum. The simulation also determines the daily volume of peak-period charging for electric buses, which is used in the strategy (below) to determine if the battery should be charged using off-peak power.

The basic operational strategy is as follows:

1. Electric buses only
    (a) If bus charging demand > generation, discharge battery to meet demand (unless off-peak and (c) applies), import if battery discharged
    (b) If bus charging demand < generation, charge battery
    (c) If battery SoC < minimum (default minimum = average daily peak-tariff period charging demand + battery parasitic demand) then charge battery during off-peak hours to above minimum level
2. Hydrogen buses only

   (a) If generation>minimum electrolyser load+10% then start up electrolyser and load follow excess generation

   (b) If generation<minimum electrolyser demand and storage level OK, then stop electrolyser

   (c) Where hydrogen storage is less than minimum requirement, then run electrolyser at full power in off-peak hours until above minimum. If storage< minimum/2 then run electrolyser during peak hours. If storage< minimum/3 then import hydrogen to storage (i.e. purchase hydrogen)

3. Mix of hydrogen and electric buses

   (a) Where a mix of buses is available, the algorithm prioritises hydrogen production on the principle described in (2) and any surplus power (i.e. that would otherwise be exported) is diverted to the battery for charging as per (1). The battery is not used to run the electrolyser.

Note that car charging demand is not taken into account when determining operating mode since the sale of electricity for charging always generates a profit due to the pricing strategy described earlier. Any car charging demand is added to the demand after all other demands and will be supplied from onsite generation or import; it is never supplied from the onsite battery.

The generation agent also calculates trading period energy totals and determines costs based on the current tariff. For simplicity, the tariff is the same every day as set out in Figure 5.7. These tariffs are based on business tariff rates analysis from a business pricing website [24] and e-Power Auctions for export [81].

Self-sufficiency

The generation agent also calculates system self-sufficiency. Three self-sufficiency values are determined:

1. excluding hydrogen imports and car charging (Equation 5.2) ;
2. including hydrogen imports and excluding car charging (Equation 5.3)
3. including hydrogen imports and car charging (Equation 5.4)

$$S_1 = \left(\frac{(E_b + E_{h1}) - E_s}{E_b + E_{h1}} \right) \tag{5.2}$$

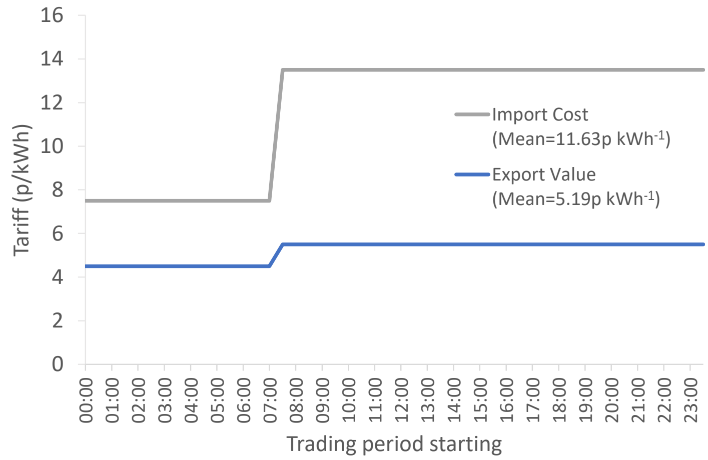


Figure 5.7: Tariffs for import and export. Off peak periods for each are defined when the tariff is less than the mean tariff.

$$S_2 = \left(\frac{(E_b + E_{h1}) - (E_s + E_{h2})}{E_b + E_{h1} + E_{h2}} \right) \tag{5.3}$$

$$S_3 = \left(\frac{(E_b + E_{h1} + E_c) - (E_s + E_{h2})}{E_b + E_{h1} + E_{h2} + E_c} \right) \tag{5.4}$$

where:

S_1	self-sufficiency index excluding hydrogen import and car charging
E_b	total electricity consumed by bus charging (kWh)
E_{h1}	total electricity consumed by on-site hydrogen electrolyser (kWh)
E_s	total electricity imported to system,excluding car charging (kWh)
S_1	self-sufficiency index including hydrogen import and excluding car charging
E_{h2}	total electricity consumed by off-site electrolysis, assuming same efficiency as site electrolyser (kWh)
S_2	self-sufficiency index including hydrogen import and car charging
E_c	total electricity consumed by car charging (kWh)

5.9 Wind agent

An agent is created for each individual wind turbine as specified during start-up. The model currently assumes a 500kW EWT turbine [85], though in principle, any

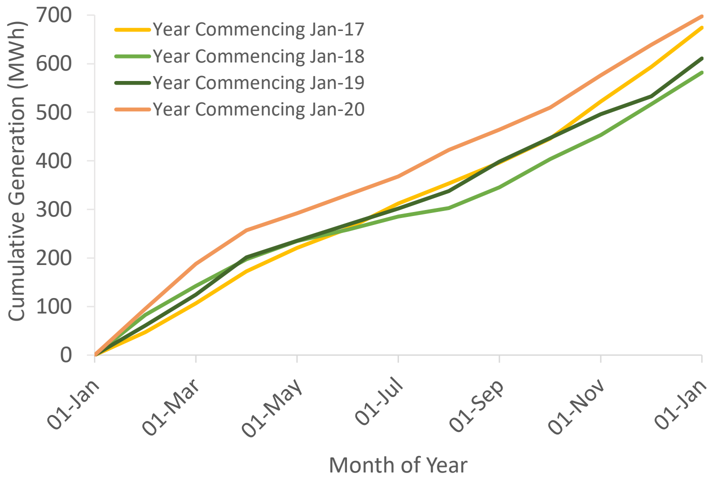


Figure 5.8: Wind turbine monthly output over 4 years, from which half hourly windspeed data was reverse engineered for the simulation, showing mix of performance over the period (sourced from HoTTWind@Longley Ltd.)

turbine power curve can be substituted (note that the turbine capacity is determined from the specified power curve at 20ms^{-1} wind speed). The wind speed data was generated by applying the as-measured turbine power-curve to the mean generation in each half hourly trading period recorded by the generation meter for a real turbine located just north of the Peak District northern edge. A total of 4 years of half hourly data has been used, which includes a range of wind conditions and for which downtime was removed (replaced with estimated data from adjacent performance). The actual monthly output from the turbine, which is a 225kW Vestas/RRB V27 on a 30m tower, is illustrated in Figure 5.8.

A wind adjustment factor can be used to modify the wind speed at each sample according to alternative hub heights or to reflect a different mean windspeed at the selected site. Whilst this will not be wholly accurate in regard to specific site wind characteristics, it does provide more granular (i.e. half hourly data) than is readily obtained elsewhere.

To ensure that the impacts of downtime are reflected in the model output, each turbine agent also has scheduled and unscheduled maintenance events. These are designed to be typical of wind turbine operations [39], and are as follows (numbers in brackets show PERT distribution parameters for event duration in hours):

- 6 month service (min=6h, max=12h, mode=8h)

- 12 month service (min=28h, max=48h, mode=32h)
- breakdown Poisson rate of 3 per annum (min=0.5h, max=336h, mode=24h)

Separate turbines have service schedules that do not overlap, though they can overlap with breakdowns on other turbines. The normal contractual target is 97% [39]; given that manufacturers will not generally want to pay damages, the actual performance is likely to be slightly better, although the guarantees would typically expire after 5 years.

The wind agent calculates the turbine output every 30 minutes and maintains a record of wind turbine availability and mean capacity factor. The generation agent contains the logic to provide trading period total generation from all wind turbines.

5.10 Solar PV agent

Solar generation is modelled in a similar fashion to wind. One solar agent is created for each inverter rather than individual panels so as to replicate downtime associated with inverter/switch gear maintenance. Inverter rating is specified at model start up, with a default of 60kW. This is not untypical of even very large solar arrays which may have many hundreds of such units, though designs with large (e.g. 500kW) inverters are also used. The solar data is based on anonymized Sheffield Live PV data from a site to the West of the Peak District, this data is only available at hourly intervals.

Each inverter agent has scheduled and unscheduled maintenance events, similar to wind, as follows:

- 12 month service (min=2h, max=8h, mode=4h)
- breakdown Poisson rate of 2 per annum (min=8h, max=168h, mode=48h)

The solar agent calculates the PV output at 30 minute intervals and maintains a record of availability and mean capacity factor.

5.11 Electrolyser agent

The electrolyser agent is based on data supplied by ITM Power as set out in Table 5.1. A budget cost of £1.3M was quoted for this unit without storage or compression. The specification is limited in some areas such as the base parasitic demand of the unit and the profile for cold-start. The ability of the Polymer Electrolyte

Membrane (PEM) electrolyser unit to closely load follow is also unclear. Whilst load-following capability may be a consideration in detailed system design and may require some additional load balancing, perhaps use of a fast acting battery system to enable the electrolyser to modulate more slowly, the model resolution (30 minute wind/1 hour solar data) renders detailed modelling of this inconsequential. Start-up times and parasitic demands are however more significant. A simple ramp-up curve is modelled which models zero output for the first 5 minutes after a cold start request, moving to 20% output at 5 minutes and then ramping linearly to 100% at 30 minutes. On unit shutdown, a cooling timer starts a countdown from 60 minutes. If a restart is called within 30 minutes then the unit is assumed to be hot and can restart from the requested load, if it is greater than 30 minutes, then the maximum demand is assumed to be the reverse of the cold start-up curve. That is, if the unit had been offline for 55 minutes, then it will restart at a maximum 20% capacity, if offline for 30 minutes it will restart at a maximum of 100% capacity. A fixed parasitic demand of 30kW, is assumed at all times. In addition, a variable parasitic demand to represent H_2 compression power is added based on a rule of thumb of 2.1% of the energy content in the hydrogen stream [30].

A maximum available power is passed to the electrolyser agent each minute from the generation agent and the operating point of the electrolyser (kg h^{-1} of H_2) is determined based on Equations 5.5 and 5.6. The current storage level is also tested and, if full, the electrolyser shuts down.

$$H_t = min\left[f_{ramp}(max\left[t_{cool} - t_{stop} + t_{start}, t_{start}\right], E_t\right] \times H_{max} \tag{5.5}$$

where:

f_{ramp}	start-up ramp function
t_{cool}	time taken for complete cool down of electrolyser (60 minutes)
t_{stop}	minutes elapsed since electrolyser stop
t_{start}	minutes elapsed since electrolyser start
H_{max}	maximum output of electrolyser in kg h^{-1}
P_p	parasitic load in kW (30kW)
P_t	power available for electrolyser use at time t, kW
C	Electrolyser hydrogen production coefficient in kg kWh^{-1}

and

$$E_t = min\left[1, max\left[E_{min}, \frac{(P_t - P_p)}{\frac{H_{max}}{(C+P_p)}}\right]\right] \tag{5.6}$$

Currently no stack degradation is modelled and no additional outage (beyond downtime when there is no available power or the storage is full) is included. The costs of maintaining stack output is included as an operational maintenance cost.

5.12 Battery agent

The battery agent is a simple storage function where the available spare generation (i.e. generation less demand) is passed to the battery function at 1 minute intervals. Operation is assumed to be instantaneous and there is no start-up delay or minimum load. A fixed parasitic load of 0.1% of the installed energy capacity is applied at all times to reflect control system demand and separate charging and discharging efficiencies (both default to 95%) are applied.

Whilst the total number of equivalent full-cycles is monitored, no degradation allowance is made; the costs of maintaining battery capacity is included as an operational maintenance cost.

5.13 Main agent functions

The main agent collects data from the various agents described previously and calculates summary data as described below.

5.13.1 Energy/fuel consumption

Electric bus energy charged is calculated in total, as a daily average and as a daily average during peak hours as summarised in Equations 5.7, 5.8 & 5.9. The later being used to determine whether the central battery should be charged using off-peak power (see Section 5.8).

$$E_e = \sum_{n=1}^{e_t} \left(E_{p,n} + E_{o,n}\right) \tag{5.7}$$

$$\bar{E_e} = \frac{1}{t_d} \sum_{n=1}^{e_t} \left(E_{p,n} + E_{o,n}\right) \tag{5.8}$$

Table 5.1: Electrolser specification sourced from ITM Power

Parameter	Units	Value	Notes
Electrolyser technology	-	PEM	
Number of electrolyser stacks	items	2.0	
Maximum hydrogen production	kg h^{-1}	21.8	1
Input power at maximum production	*kW*	1270.0	
System efficiency	kWh kg $^{-1}$	56-60	2
Output pressure	barg	20.0	
Water consumption	l kg^{-1}	20.0	3
Load range	%	20-100	
Cold start time	s	300.0	4
Warm start time	s	30.0	
Modulation	s	2.0	
Hydrogen purity - water	H_2O ppm	<5	
Hydrogen purity - Oxygen	O_2 ppm	<5	
Ambient temperature range	°C	-15 to +40	

Table notes:

1. Theoretical maximum based on assumed environmental conditions and input power.
2. System efficiency is an estimate dependent on environmental conditions, ambient temperature, usage profile, and operating pressure.
3. Includes the expected rejection rate from the water purification system. This figure is dependent on the quality of the incoming feed water.
4. Denotes the time taken for the electrolyser to first begin producing gas, not to reach its maximum operation

General notes from ITM Power:

- The values in the table are averages. The performance will vary as individual components of the balance of plant turn on and off and as the external temperature changes. The figures are based on an external temperature of 15°C.
- The figures are based on the system's start-of-life; the system is expected to gradually degrade over its lifetime. The degradation rate would depend on the exact usage profile.
- The figures assume that the system is operating at its normal process temperature. During a cold start, it can take several minutes before the water process temperature reaches normal levels and the performance is optimised.

$$\bar{E_e} = \frac{1}{t_d}\sum_{n=1}^{e_t} E_{ph,n} \tag{5.9}$$

where:

E_e	Electric bus energy in kWh
e_t	number of electric buses
E_p	Energy charged during peak hours in kWh
E_o	Energy charged during off-peak hours in kWh
E_{ph}	Energy charged at hub (private wire network) during peak hours in kWh
t_d	Number of days

For hydrogen buses, the quantity of hydrogen filled at the depot is summed across all buses and a daily average is also determined for storage size calculations, as per Equations 5.10 and 5.11.

$$M_h = \sum_{n=1}^{h_t} M_n \tag{5.10}$$

$$\bar{M_h} = \frac{1}{t_d}\sum_{n=1}^{h_t} M_n \tag{5.11}$$

where:

M_h	Mass of hydrogen consumed in kg
e_t	number of hydrogen buses
EM_p	Energy charged during peak hours in kWh
E_o	Energy charged during off-peak hours in kWh
E_{ph}	Energy charged at hub (private wire network) during peak hours in kWh
t_d	Number of days

5.13.2 Costs and net present value

Costs are accrued to running totals as the simulation progresses. The sources of costs used in the model are given in Table 5.2. In the case of hydrogen purchase costs, Drive Electric [70] indicate pump retail prices of about 10.00£ kg^{-1} whereas the H21 report [191] indicates a future retail price for blue hydrogen of 7.2p kWh^{-1} (exc.VAT) or about 2.80£ kg^{-1}. As such, 5.00£ kg^{-1} is selected as a reasonable current estimate for imported bulk hydrogen.

Table 5.2: REVIT cost data

Item Description	Cost	Cost basis	Source
Depot charger	20,000.00	£ unit^{-1}	Siemens
Rapid charger	20,000.00	£ unit^{-1}	Siemens
Hydrogen dispenser	5,000.00	£ unit^{-1}	ITM
Car charger CAPEX	1,000.00	£ unit^{-1}	EVBox Quotation
Charger maintenance	200.00	£ unit^{-1}y^{-1}	EVBox/Engie Quotation
Electric bus	400,000.00	£ unit^{-1}	Caetano
Hydrogen bus	525,000.00	£ unit^{-1}	Caetano
Wind CAPEX	1,200.00	£ kW^{-1}	BEIS [58]
Wind maintenance - fixed	23,500.00	£ MW^{-1}y^{-1}	BEIS [58]
Wind maintenance - variable	6.00	£ MWh^{-1}	BEIS [58]
Solar CAPEX	800.00	£ kW^{-1}	BEIS [58]
Solar maintenance - fixed	6,700.00	£ M^{-1}y^{-1}	BEIS [58]
Solar maintenance - variable	.00	£ MWh^{-1}	BEIS [58]
Battery CAPEX	195.00	£ kWh^{-1}	Bloomberg [26]
Battery opex	.33	p kWh^{-1}	World Energy Council [95]
Electrolyser CAPEX (inc. compression)	90,000.00	£ kg^{-1} h^{-1}	ITM Quote + Jovan [120]
Electrolyser maintenance - fixed	1,400.00	£ kg^{-1} h^{-1} y^{-1}	Colella [46]
Electrolyser maintenance - variable	.15	£ kg^{-1}	Colella [46]
Hydrogen storage	2.00	£ kg^{-1}	James [118]
Hydrogen delivery	5.00	£ kg^{-1}	Drive Electric [70] and H21 Leeds [191]

NPV is calculated on a monthly rolling basis as per Equation 5.12.

$$NPV_t = (NPV_{t-1} - A_{d,t-1}) + \frac{R_t - C_t}{D^t} + A_{d,t} \tag{5.12}$$

where:

NPV_t = Net Present Value at month t
$A_{d,t}$ = Depreciated value of assets at month t
R_t = Revenues in month t (power sales and charging sales)
C_t = Costs in month t (CAPEX + maintenance + power imports + H_2 imports)
D^t = Discount rate (monthly) raised to power of number of months

Note that the import costs include the costs of any remote electric bus charging events, although in the case study presented, no such events exist.

Chapter 6

REVIT case study definition and model validation

REVIT is novel techno-economic model encompassing transport as well as energy generation and storage. Interactions between agents are limited to direct communication of data, such as charging cost from the car agent to the generation agent and bus-orders transferred to buses by the scheduling agent. In regard to validation, it is thus reasonable to take a high level view of each agent and determine whether the outputs from that agent are appropriate and realistic for the data inputs. In regard to overall performance, aspects of the simulation results can be compared to other, similar, models of electric and hydrogen bus operation. It is appropriate to consider the validation in the context of the case study to be examined, hence in this Chapter, the specific case study and associated data sets are introduced and each agent is then reviewed and compared to other relevant data to confirm that the model is operating appropriately.

6.1 Case study definition

In this section the bus routes and bus types, parking and charging provision and base renewable generation and storage capacities employed for the case study are introduced. The study was based on a PnR hub facility at a prospective development known as 'Peak Resort' located off the A61 near Unstone Green in North East Derbyshire [44]. The site is a potential commuter hub for workers in Sheffield and Chesterfield and a tourist gateway for the Peak District National Park. Furthermore, it is located just outside of the park, adjacent to an industrial area, and considered suitable for wind and solar generation. An existing bus depot is located at the same A61 junction and is thus considered to be within a private wire

Figure 6.1: Map showing region of case study with bus stops (red bars). Rectangular blocks are positions of buses at stated time.

network encompassing the hub and generation; see Figure 6.1.

The case study is run over a period of 12 years which is regarded as an industry norm for 'first life' of buses [210].

6.1.1 Bus stops, routes and schedules

Table 6.1 lists all the bus stops included in the case study simulation. Whilst all bus stops can also be specified to include charging provision, the model currently only permits buses to charge at the depot, hub and one-way final destination stops; the only location this is used in the model is Sheffield bus station, which forms a destination for one route. Stop '0' is defined in the model as the depot and stop '1' the hub.

6.1.2 Bus routes and schedules

Table 6.2 sets out the bus schedules. They include 'commuter' routes to the centre of Chesterfield and Chesterfield hospital and to Sheffield together with a Chesterfield station 'shuttle' service and two longer Peak District routes one of which operates only at weekends; this example, route 6, is presented in Figure 6.2. The stops required for each route are defined in Table 6.3. Stop numbers refer to the bus stop ID from 6.1; note that -1 is an end of route indicator. In this case study,

Table 6.1: Bus stops

ID	Name	Latitude	Longitude	Private Wire	Depot Chargers	Rapid DC Chargers	Hydrogen Stations	Parking Spaces	Car Chargers
0	Chesterfield Depot	53.272	-1.441	Yes	30	0	2	0	0
1	Peak Resort Hub	53.274	-1.444	Yes	0	10	1	150	50
2	Cavendish Street	53.237	-1.426	No	0	0	0	0	0
3	Lordsmill Street	53.234	-1.424	No	0	0	0	0	0
4	Chesterfield Hospital	53.236	-1.397	No	0	0	0	0	0
5	Chatsworth House	53.229	-1.611	No	0	0	0	0	0
6	Haddon Hall	53.192	-1.651	No	0	0	0	0	0
7	Bakewell	53.213	-1.675	No	0	0	0	0	0
8	Monsal Trail Bikes	53.233	-1.676	No	0	0	0	0	0
9	Wardlow	53.269	-1.729	No	0	0	0	0	0
10	Chesterfield Station	53.238	-1.420	No	0	0	0	0	0
11	Toll Bar - Stoney Middleton	53.276	-1.657	No	0	0	0	0	0
12	Unstone Green	53.287	-1.441	No	0	0	0	0	0
13	Dronfield Station	53.301	-1.468	No	0	0	0	0	0
14	Meadowhead	53.328	-1.475	No	0	0	0	0	0
15	Woodseats	53.342	-1.478	No	0	0	0	0	0
16	Royal Hallamshire	53.377	-1.493	No	0	0	0	0	0
17	University	53.380	-1.489	No	0	0	0	0	0
18	West Street	53.381	-1.475	No	0	0	0	0	0
19	Sheffield Bus Station	53.380	-1.464	No	0	5	0	0	0
20	Owler Bar	53.298	-1.560	No	0	0	0	0	0
21	Sunrise View	53.317	-1.623	No	0	0	0	0	0
22	Hathersage	53.330	-1.656	No	0	0	0	0	0
23	Bamford	53.348	-1.690	No	0	0	0	0	0
24	Ladybower	53.371	-1.697	No	0	0	0	0	0
25	Fairholmes	53.400	-1.743	No	0	0	0	0	0
26	Ladybower2	53.371	-1.697	No	0	0	0	0	0
27	Bamford2	53.348	-1.689	No	0	0	0	0	0
28	Hope	53.347	-1.741	No	0	0	0	0	0
29	Castleton	53.344	-1.778	No	0	0	0	0	0

Table 6.2: Bus route schedule

	Route	Mon-Fri		Sat		Sun		Ave. Speed	Frequency	Min. Dwell	Reversal
Number	Name	Start	End	Start	End	Start	End	kmh^{-1}	min	min	
1	Hub-Hospital	07:00	21:00	08:00	20:00	09:00	18:00	50	30	5	True
2	Hub-Peak WE	00:00	00:00	07:00	16:00	08:00	17:00	40	60	15	False
3	Hub-Station	07:00	20:00	08:00	19:00	07:30	19:30	50	30	15	True
4	Hub-Sheffield	06:30	19:00	07:00	18:00	07:30	19:00	40	20	15	True
5	Hub-Peak WD	09:30	12:30	00:00	00:00	00:00	00:00	40	180	15	False
6	Hub-NorthPeak	00:00	00:00	07:15	15:15	07:15	15:15	40	60	15	True

all routes start at the hub (stop 1), but this is not essential. Only sufficient stops to define the route need be included, but the model adds 1 minute to the journey time for each scheduled stop, thus all major stops where significant passenger flow might occur are included. The simulation automatically routes buses by the fastest available route between stops at the average speed defined in Table 6.2 using the simulation software provider's routing server.

6.1.3 Bus types

Bus parameters are set out in Table 6.4 for 3 buses. The data for buses 2 & 3 were sourced from Caetano [210], bus 1 is a model manufactured by Optare, with

Table 6.3: Bus route definitions

Route Number	Start Point	Route Stop (see Table 6.1) 1	2	3	4	5	6	7	8	9	10	11
1	1	2	3	4	-1							
2	1	5	6	7	8	9	11	1	-1			
3	1	10	-1									
4	1	12	13	14	15	16	17	18	19	-1		
5	1	5	6	7	8	9	11	1	-1			
6	1	20	21	22	23	24	25	26	27	28	29	-1

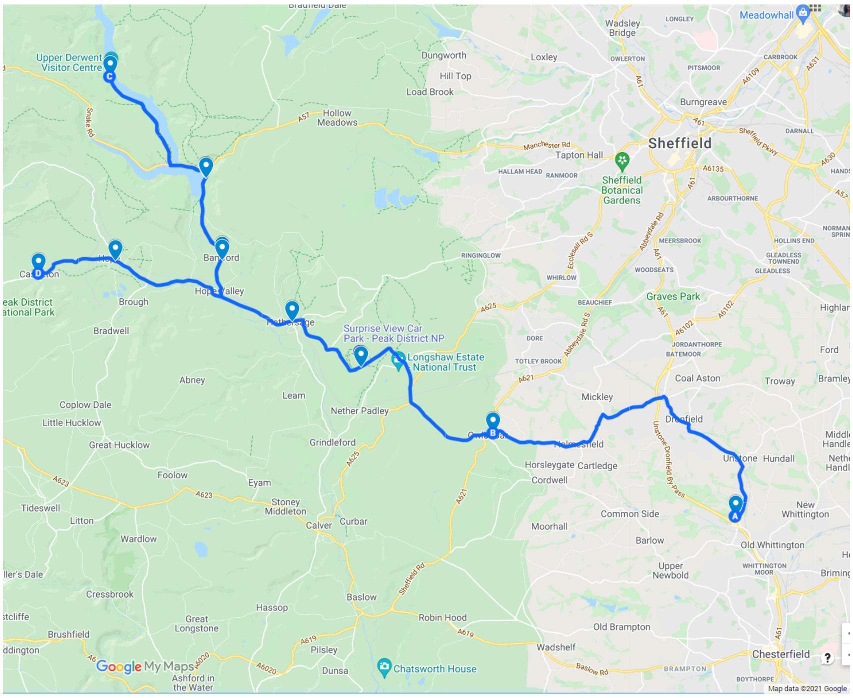


Figure 6.2: Example bus route - Route 6 for North Peak District. Only major stops included to allow automated routing; a 1 minute delay is added for each route stop.

Table 6.4: Bus specifications

Type	Fuel	Battery Capacity kWh	Electric Efficiency km/kWh	Depot Charge Rate kW	Depot Charge Efficiency %	Rapid Charge Rate kW	Rapid Charge Efficiency %	Hydrogn Bus Fuel kg	Hydrogn Bus Efficiency km/kg	CAPEX £	Maint-enance £/km	Major Service £
1	electric	220	0.60	44	90%	100	92%	0	0	350000	0.02	65000
2	electric	385	0.75	150	92%	150	92%	0	0	400000	0.02	110000
3	hydrogen	0	0.00	0	0%	0	0%	38	15	525000	0.03	35000
3*	hydrogen	44	0.60	22	90%	0	0%	38	15	525000	0.03	35000

pricing estimated from Caetano costs. Note that bus 3* contains the actual parameters (battery size and charging) for hydrogen bus 3. In principle, it is possible to charge the hydrogen bus battery at the depot, however, the bus operates much as a non-plug-in hybrid car; i.e. the battery is used to ensure that the hydrogen fuel cell can run at a flat output and optimum efficiency for most of the time. It can also be used at the start of the day when the cell may not be up to temperature and cannot deliver full power. However, without a detailed bus drive-train model and simulation of route gradients and speed profiles, it is not possible to determine the state of charge of the hydrogen bus battery at any given time. Thus for simplicity, the battery is ignored and the bus modelled as a pure hydrogen vehicle with a fixed efficiency.

The number of each type of bus at the start of the simulation is not shown in the table as this varies across scenarios.

6.1.4 Car arrivals, parking and charging

A schedule defines the rate at which cars arrive at the hub by hour of the day separately for weekdays and weekends as illustrated in Figure 6.3. This data is postulated based on the following assessment:

- There are 16 commuting bus departures on or before 9.00am each morning
- Each bus has 64 seats, assume a notional hub departure occupancy of 50%
- Each car arrival has 1.1 passengers (based on 10% of car commuters being passengers [64])
- Therefore to achieve 50% occupancy, there are 19 cars per bus, thus 304 car arrivals between 6.00am (assumed as earliest) and 9.00am (assumed latest) with a peak between 7.00am and 8.30am.
- Car drivers choose to charge between once every 2 days and once every 3 days, which leads to an assumption of 125 parking spaces being equipped with chargers.

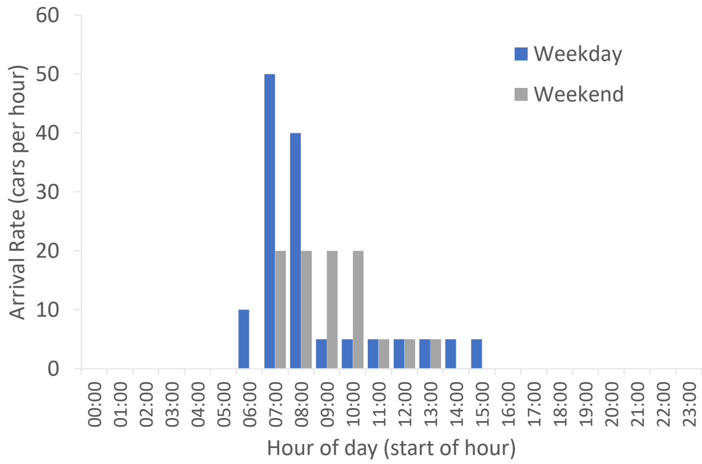


Figure 6.3: EV arrivals at commuter hub for weekdays and weekends. Note: the validation model uses 150 parking spaces and 50 charging spaces and correspondingly lower car arrivals (ca. 1/3 of those presented here.)

However, for the purposes of the validation hub parking and car arrivals were reduced to increase execution speed; only 150 parking spaces with 300kW of PV and 50 charging bays were included and arrivals were reduced proportionately.

6.1.5 Renewable generation and storage

The base study includes 2 x 500kW wind turbines plus 700kilowatts peak installed capacity (kWp) of solar PV (2kWp x 350 parking spaces). No adjustments are made to the wind or solar outputs.

The minimum storage capacities are a 1,000kWh battery and 2,000kg of hydrogen storage. The minimum battery storage was selected due to the current high cost of such systems, whilst the hydrogen storage was chosen based on a hydrogen delivery vehicle carrying 900kg [30] of hydrogen, thus ensuring that there is always adequate volume to offload a full tanker, whilst retaining sufficient reserve volume. In practice, many of scenarios are run with storage capacities based on days of energy demand for the highest use day.

A single 21.8kg h^{-1} electrolyser is used in the base hydrogen bus models as set out in Table 5.1.

6.2 Model validation

In this section, each agent type is reviewed against a number of tests to validate functionality and confirm that model outcomes are realistic and robust.

6.2.1 Bus agent functionality

The bus operation is the most complex aspect of the model and here a number of bus parameters are presented and compared to expectations based on either other modelling results, information provided by manufacturers or direct analysis.

The electric bus base efficiency is set at 0.75km kWh^{-1} (see Table 6.4). After a 12 year model run, the total energy charged for an all electric bus scenario is 18,554,708kWh over a distance of 12,387,434km. Adjusting for charging efficiency of 92% (see Table 6.4), gives an E-Bus as-charged efficiency of 0.73km kWh^{-1}. The ambient temperature adjustment factor will generally result in slightly lower performance than the base figure. Göhlich et al. [100] quote a figure of 0.55km kWh^{-1} in their 2018 paper, based on somewhat more extreme (both winter low and summer high) Berlin temperature conditions. It is not clear whether this is vehicle efficiency or as-charged efficiency; the model vehicle efficiency here is 0.67km kWh^{-1}. Furthermore, with battery energy density increasing, vehicle weights are also reducing, improving efficiency. Thus the more recent figures quoted by Caetano may now be realistic.

Caetano forecast electric bus battery life as about 6 years and 70% SoH dependent on utilisation and with typical annual distances of 60-100,000km [149]. The model forecasts reaching 70% SoH after around 64,000km with times ranging from 6-9 years depending on utilisation. Thus whilst at the lower end of reported performance, it does fall within realistic bounds.

The base hydrogen bus efficiency is 15km kgH_2^{-1} (see Table 6.4). The model forecasts 775,835kgH_2 consumed over a 12 year life with 11,577,467km travelled, giving an efficiency of 14.92km kgH_2^{-1}. Since the hydrogen buses only consume additional power on hot days, this is also consistent with expectations.

6.2.2 Route data

The routes were initially set out in Google Maps. To confirm that the buses are following similar routes and at a sensible average speed, route 6 was analysed as follows:

- 'Google Maps' route length = 49.4km
- 'Google Maps' route time 62 minutes (by car)

- Model route length = 51km
- Model route time = 82 minutes (37.3km h^{-1} vs 40km h^{-1} route speed)

The average speed will be less than the set route speed due to 1 minute being added for each stop. The modelled outcomes are thus consistent with alternative mapping/routing data and therefore bus availability, which is primarily influenced by route length and duration, will be appropriate.

6.2.3 Scheduling and bus creation

Bus selection strategy

Analysis of the bus selection strategy is included here since it guides the strategy used in the case study. The simulation includes a number of selection strategies for buses as outlined in Section 5.5. The impact of these strategies is minimal for hydrogen buses since they have adequate range for all routes over the 12 year period, although the lowest total distance travelled should result in better economics since less hydrogen will be required. However, for electric buses the strategies can have quite different outcomes as illustrated in Table 6.5 for the base model run over 12 years with all electric buses. The closest to route start strategy results in the lowest bus requirement for electric buses and the lowest overall distance travelled (therefore the optimum outcome for hydrogen buses). Figure 6.4 shows how the numbers of buses required increase over time for each strategy. The random and closest/lowest mileage scenario deliver the same results because, under the latter, buses are effectively being chosen to deliver an even mileage across the fleet, which is equivalent to randomly selecting a bus. Selecting the lowest mileage bus results in more relocation journeys and consequently higher total distance travelled. This is also true of the highest current range option, which will tend to draw buses from the depot each time a new route is started. It also results in a more even increase in km travelled by each bus, meaning that the available range falls more evenly across the fleet. The closest to route start option, by virtue of the fact that Anylogic always starts with 'bus 1' and works up at the start of each day, effectively creates a large divergence in the kilometers travelled by each bus and means that when the range of 'bus 1' is no longer adequate for the longest journey, it will be selected for shorter routes instead, but later bus additions still have adequate range. Thus this option is almost the opposite of the lowest mileage strategy; i.e. the simulation is usually choosing the highest mileage bus able to complete the route. Since the closest to start strategy results in the optimum solution for both electric and hydrogen buses, this was used throughout the case study.

Table 6.5: Performance of bus selection strategies

Bus selection strategy	Total buses (At end Year 12)	Utilisation %	Total Distance km
Closest to route start	18	17.3	12,379,963
Closest unless at depot, then lowest mileage	22	14.3	12,591,104
Lowest current mileage	22	14.4	12,656,997
Highest current range	25	12.7	12,667,346
Random	22	14.3	12,591,104

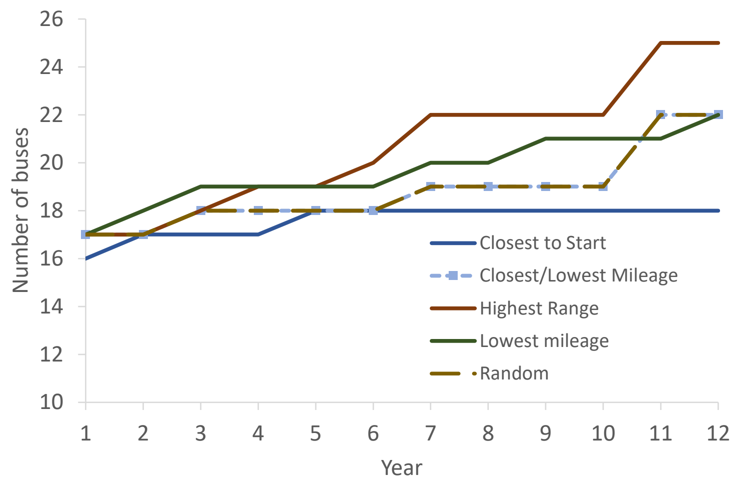


Figure 6.4: Number of buses required under each selection strategy at the end of each year (all electric bus solution).

Scheduling performance

The distance travelled by a bus in a year is indicative of its utilisation and is an indication of the effectiveness of scheduling; poorly scheduled buses will not spend so much time on active routes. The average bus in the model travels 65,863km per year. This is consistent with the lower end of expectations [149], but given that the simulation includes rural routes with low repetition, this appears reasonable. Thus the scheduler generates a satisfactory regime for bus dispatch.

Göhlich et al. [100] report a requirement for 7 diesel buses or 7 opportunity-charged buses vs 12 depot-charged buses to cover the same route schedule, a factor of 1.7. In this simulation the electric buses adopt a hybrid depot/opportunity strategy with only limited opportunity charging available. When hydrogen buses are used (which have the same range as equivalent diesel buses), 15 such buses are required in total, where an all-electric solution is adopted, 18 buses are required, a factor of 1.2. Given that buses are able to re-charge at the hub during the day, and frequently do so, this appears to be a reasonable number of additional buses.

6.2.4 Wind and solar agents

The wind and solar generation agents operate in a similar fashion. Figure 6.5 shows a randomly selected April week of output from both generation sources. The solar generation is determined directly from the source data with a scaling factor and thus requires little validation; the chart shows the system operating only during daytime periods and with a peak of a little over 200kW, which is consistent with a 300kWp system. The wind profile is a more complex function, with wind data reverse-engineered from the original turbine output and a different turbine power curve applied to produce the simulated generation. However, plotting the same week of output data from the source turbine illustrates that the model is producing a similar profile. The source turbine peaks at 185kW (82% of rated output), whilst the modelled turbine peaks at 760kW (76% of rated output); this is reasonable given that the turbine power curves are different and the wind speed at this time is below that at which maximum output occurs for both turbines. Thus the generation profiles can be considered representative of what might be achieved in practice.

Over the 12 years modelled in the case study, the wind turbine capacity factor is 31.8%. This is relatively high for UK onshore wind, which averages 26.2% [57], but is consistent with the performance of the turbine from which sample data has been used. The turbine availability averages 97.1% over 12 years, which is consistent with manufacturer performance guarantees of 97%.

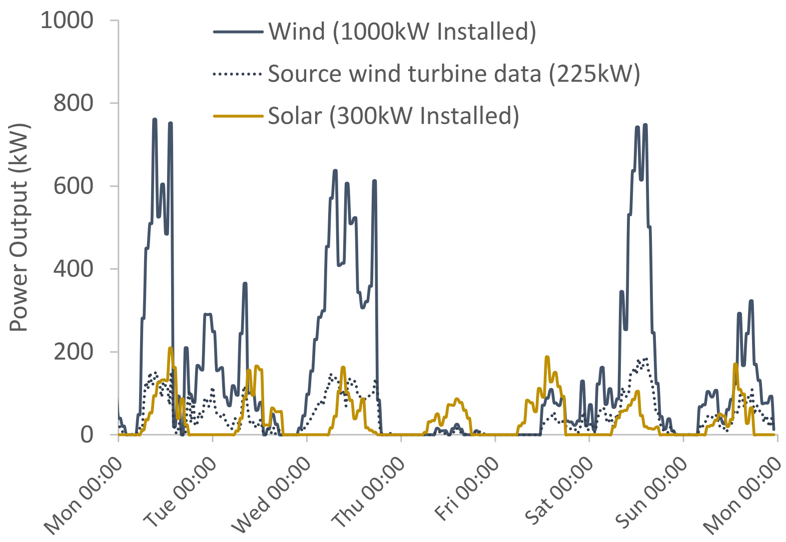


Figure 6.5: Random April week of generation output from simulation for base case generation of 2 x 500kW wind turbines and 300kW of Solar PV

For the solar generation, the capacity factor is 9.24%; this compares to 9.8% from the NREL solar output calculator [159]. However, the NREL solar data is based on Finningley, which is likely to receive slightly higher sunshine hours being further east and subject to lower cloud and rainfall from the prevailing westerly winds. The solar system availability is 98.6%.

6.2.5 Battery agent

The central battery operation over 5 days of the case study, picked for their variability of operation, is illustrated in Figure 6.6. Generation, SoC and battery power flow are plotted as 5 minute samples (not averages), the bus charging demand is a 0.5h (trading period) average, which accounts for reduced values compared to battery discharge when all charging is from the battery. The operational modes of the battery are as specified and described below.

A - Initially overnight bus charging demand is met from battery + generation, as charging demand falls, battery swings from discharge to charge mode restoring full SoC

B - Daytime rapid charging demand is met from site generation, battery SoC maintained close to 100% as demand varies.

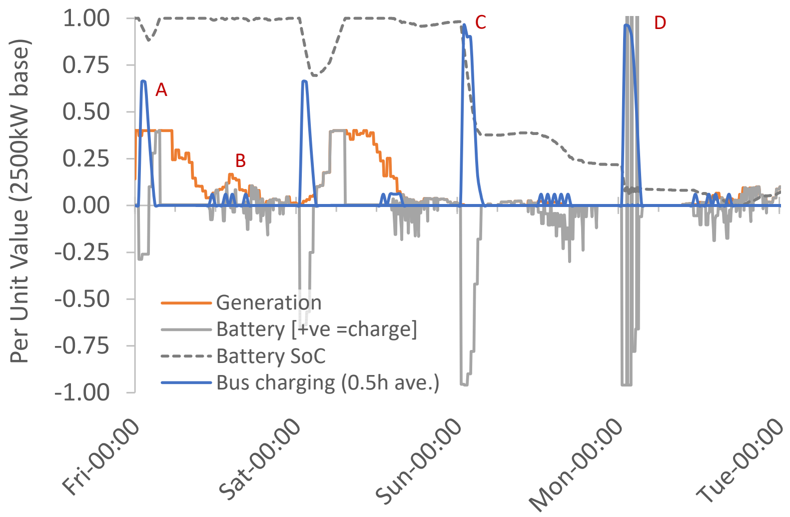


Figure 6.6: Battery operation over 5 days of different operational modes

C - Night time bus charging met entirely from battery as no generation, the following day's charging demand is also met from battery discharge (between C and D).

D - Storage falls below minimum threshold (One day of peak charging demand) resulting in battery being charged from off-peak power since no generation available. The battery is capable of swinging from full charge to full discharge in less than one model time-step and the hysteresis is relatively small hence overnight swings from full charge to full discharge as buses charge at a lower rate than the battery can recharge.

6.2.6 Electrolyser agent

The electrolyser operation over a period of 5 days, picked for the variety of operational modes, is illustrated in Figure 6.7. The full load power of the electrolyser (with parastic demand) is 1370kW; the flat tops to generation (see A on Figure) are when there is no solar, but full-load wind (1000kW = 0.77pu generation), so the electrolyser is not dispatched to full capacity. The operation functions as specified, as can be seen at the following points:

A - Storage reaches maximum capacity and electrolyser shuts down

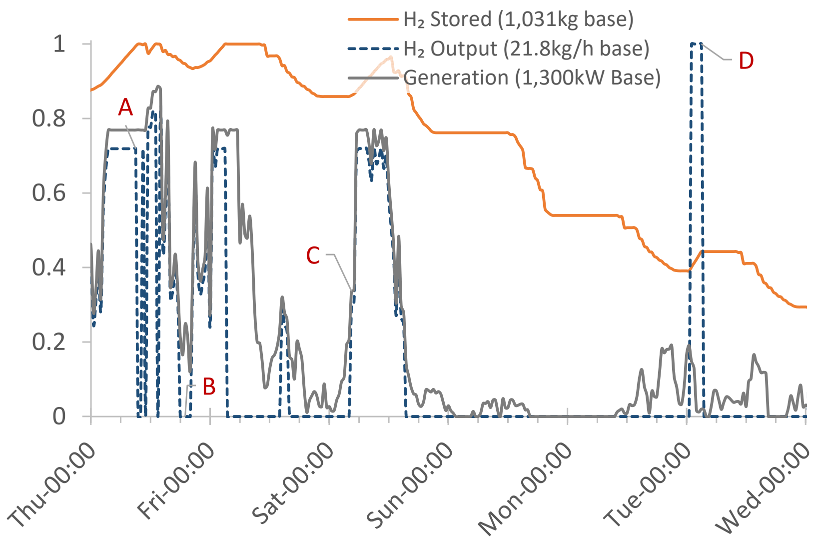


Figure 6.7: Electrolyser operation over 5 days of different operational modes

B - Available generation drops below minimum electrolyser load when sufficient hydrogen in store; electrolyser shuts down

C - Electrolyser ramping from cold start and then load following

D - Storage drops below minimum level, off-peak overnight operation of electrolyser restores level to minimum + daily demand (hysteresis function)

Note that hydrogen buses return to the depot relatively early since there are frequently circumstances where there are enough buses on routes with sufficient range to enable completion of the day's schedule. This means that buses start refuelling from the middle of the day - the difference between Sunday (when there are fewer routes operating for a shorter period and therefore many early depot returns) and weekdays is clearly seen by the more rapid decline in hydrogen stored during the day between C and D when no production is occurring. There are occasions when the scheduler uses a bus that has returned to the depot because it is closer to the route start when dispatch is requested.

6.2.7 Car agents

The modelling of the car agent's operation is relatively simple; the validity of the algorithms can be tested by exploring the the total number of charging events, mean energy charged and cost as follows.

Charging events Over the 12 year's modelled, the total number of charging events, measured as cars using a charging space, is ca. 251,000. This corresponds to 57 per day and is consistent with 50 charging spaces used during validation runs since some may get used more than once in a day.

Mean energy charged The mean energy charged during a parking session ranges from 9.05kWh to 12.69kWh. The variability is related to the installed generation capacity (particularly solar since it is active when cars are present) and the number of electric buses in the fleet, since these may be recharging during the day. This reduced availability of onsite generation for charging increases the charging tariff and thus reduces the number of cars willing to charge.

Mean unit cost The mean unit cost must lie between the marked-up export value (5.5p kWh^{-1} +25% - daytime tariff since that is when cars are parked) and the peak site import cost (13.5p kWh^{-1} +25%). The mean price will vary depending on site generation and the model produces values between 9.04p kWh^{-1} and 14.21p kWh^{-1} which are consistent with the expected range.

Chapter 7

BEVI results and discussion - policy and EV adoption

In this chapter, the results of a suite of analyses conducted using the BEVI model, with new EV creation and cost reduction, are presented. The questions to which answers are sought are:

1. Which policies are most effective at driving EV adoption?
2. How can such policies be tailored to maximise social equity?
3. How do differing policies impact on carbon emissions reductions?
4. What is considered a likely set of policies and what are their impacts?

The installation rate of chargers may also impact on adoption, yet also be affected by government policy decisions, since the private sector is more likely to invest in charging provision when there is confidence of a growing market. To avoid the fixed rate charger installations having an impact in addition to policy, these initial assessments are made with a rapid roll out of chargers that does not inhibit adoption. The effects of charger deployment are explored in Section 7.4. In these analyses, home charging and public charging are assumed to have the same tariff, such that the impacts of home charging access are minimised. Variations in tariff are explored later.

7.1 Which policies are best at driving adoption?

Which policies are most effective at driving EV adoption?

Given that the UK Government, along with others, has plans to introduce bans on the sale of fossil fuelled vehicles, it is appropriate to consider how such bans effect adoption in the simulation and compare less draconian measures to assess their effectiveness. The Government has introduced a number of incentives including grants for charging infrastructure and a capital grant for BEVs; this later grant was reduced from £3,500 to £3,000 in 2020 and further to £2,500 in 2021. There are also conditions on the purchase price of the vehicle, with only cars under £50,000 eligible after the 2020 reduction and those under £35,000 after 2021. The base cost of cars in the model is set at the list price less the grant in 2019. However, since the model is applying car cost reductions and there are indications that manufacturers are also responding to the thresholds [10], the changes in grant are not implemented in the simulation.

7.1.1 ICE vehicle sales bans

In this section, the impact of proposed UK policy for ICE vehicle sales bans, initially proposed for 2040, but recently brought forward to 2030, is explored. No legislation has yet been introduced to implement this pledge. The latest variant includes banning of hybrid vehicles later in 2035; the initial analysis here does not incorporate this phased approach, with only BEVs being permitted after 2030 or 2040.

Figure 7.1 compares the revised model results with the existing EV and ICE parity cases presented in Figure 4.12 and the lowest and highest forecast cases, 'steady progression' and 'consumer transformation' respectively, from the National Grid Company's 2020 Future Energy Scenarios document [158]. NGC include an estimate of MaaS adoption for the different scenarios; the adoption curves are presented here as a fraction of expected number of vehicles as that changes over time under the NGC scenarios. There is no significant divergence in total vehicle numbers before 2040 in any of the NGC scenarios. The 'Consumer Transformation' scenario is the most aggressive MaaS estimate with 6.3 million autonomous vehicles in use by 2050; there are currently 31.7 million cars in the UK.

The analysis indicates that a ban in 2040 has little, if any, impact on uptake since consumers are by this time already purchasing BEVs as the preferred power train, with 79% of cars on the road being BEVs by 2045. However, a ban introduced in 2030 does accelerate adoption resulting in some 96% of cars on the road being fully electric by 2045. This modelling does not include any additional media coverage generated as a result of the ban being introduced. In order to simulate the effect of this, combined with a longer term public awareness campaign, additional

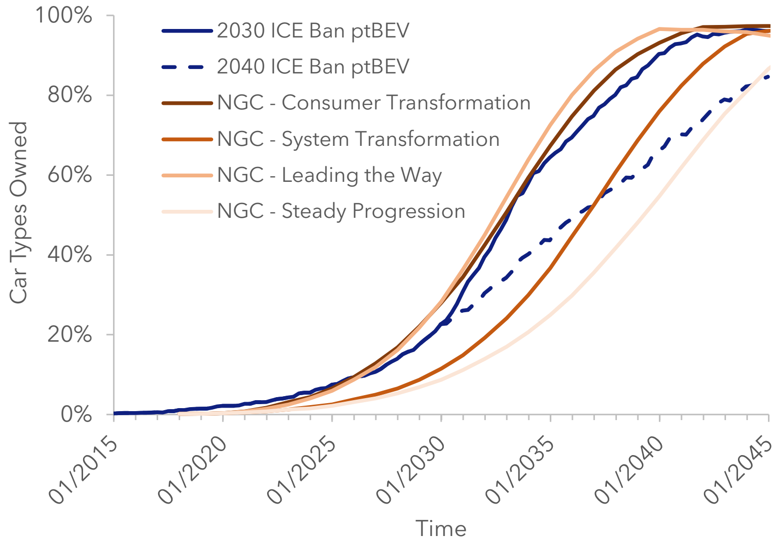


Figure 7.1: Impact of 2030 and 2040 ICE vehicle sales bans on BEV market share

'generic' EV adverts were added to the simulation from 2021 as shown in Figure 7.2 for the 2040 ban scenario (the 2030 ban results in a jump to 100% EV adverts in 2030). The figure shows how EV advertising is already increasing rapidly from 2020 due to the introduction of new models, though without the 'generic' boost, there is a sharp decline at 2022 as extra new model introduction advertising falls away. The impact of this additional advertising is illustrated in Figure 7.3. Whilst the increase in sales in transitory, with both 2030 and 2040 bans ultimately arriving at the same penetration as without bans, accelerated early adoption broadly matches that presented in the most optimistic NGC scenarios illustrated in Figure 7.1.

7.1.2 Scrappage schemes

Whilst scrappage schemes are often mentioned in the media, and have been employed in the past, the focus was then to boost car production as much as to reduce emissions [33]. Whilst some modelling studies have suggested scrappage schemes can deliver rapid emissions reduction benefits [23, 130] others have questioned the value of such schemes from an environmental perspective [29].

Figure 7.4 illustrates the impact of three scrappage schemes. In all cases, the schemes apply only to cars over 8 years old and the owners previous car is removed from the simulation. The "£3k all-car" introduces an effective £3k reduc-

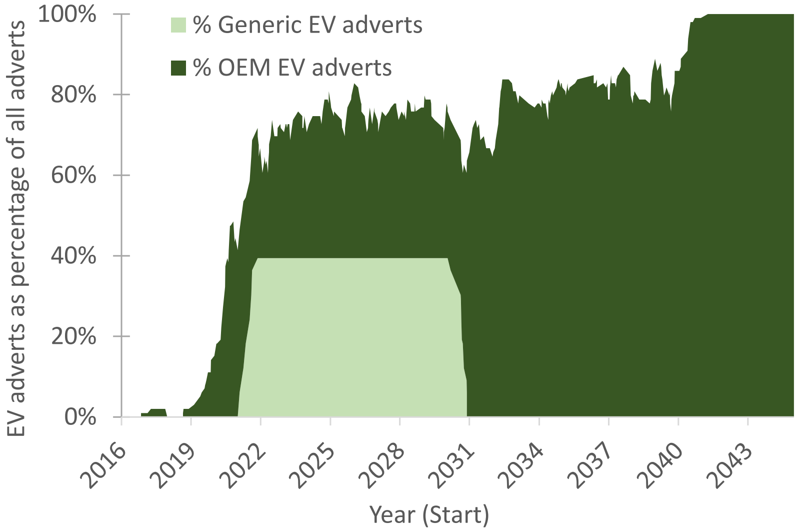


Figure 7.2: Share of BEV adverts from original equipment manufacturers (OEMs - car makers) and additional generic advertising

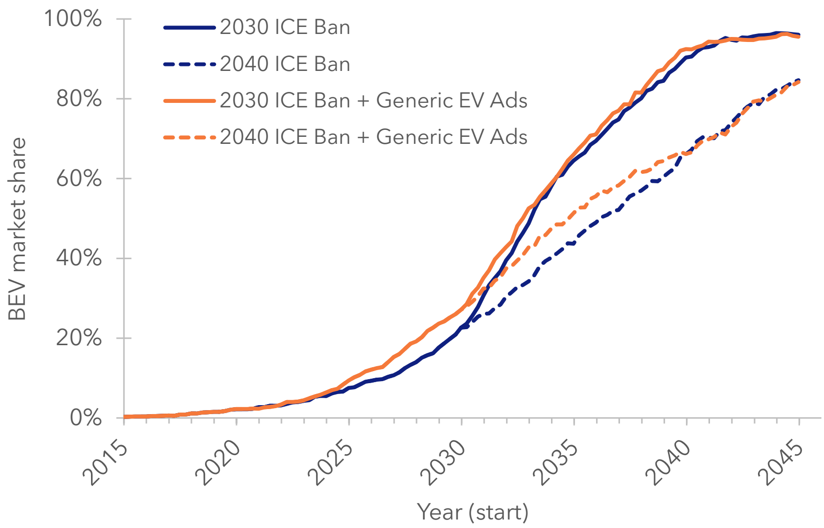


Figure 7.3: Impact of increased EV advertising on market share under the 2030 and 2040 ICE ban scenarios

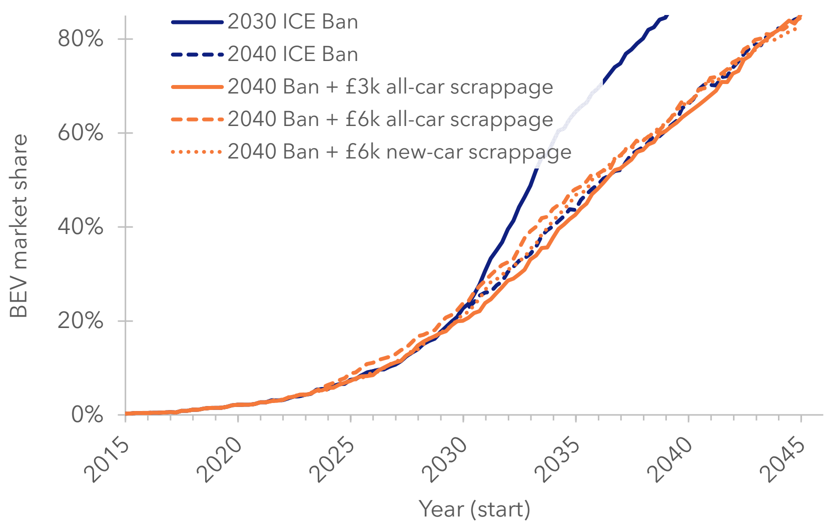


Figure 7.4: Impact of three different scrappage schemes on BEV adoption

tion in the cost of any (new or used) BEV purchase, "£6k all-car" increases the payment to £6k and "£6k new-car" only applies where the purchaser is replacing their car with a new BEV. A £6k scrappage fee is three times that offered under the 2009 diesel scrappage scheme, but was reportedly under consideration by the UK Government in 2020 [5]. The results are mixed, but with little overall impact. The £6k all-car scheme is effective in the early years, where BEV costs are high and buyers are often environmentally driven (i.e. buyers would like to purchase a BEV but are unable to afford one). The £3k scheme does not appear to make sufficient difference to the driver's cost benefit analysis to drive change. In fact, it reduces total BEV numbers in the early 2030's as it enables drivers to switch to a higher-range, used, BEV without the need to purchase new.

With the new-car only scheme, there is little perceivable difference in adoption. This is because most new car purchases are made by either fleets, where TCO dominates the decision process and there are no old cars to trade in, or relatively wealthy individuals who are similarly unlikely to have a sufficiently old car. A potential deficiency in the model here is that multi-car families might, in practice, choose to trade in an older 'second car' to obtain a new BEV whilst retaining an existing vehicle (ICE or otherwise) as a second car. Since the model works on individuals' behaviours, rather than those of households, this scenario cannot arise.

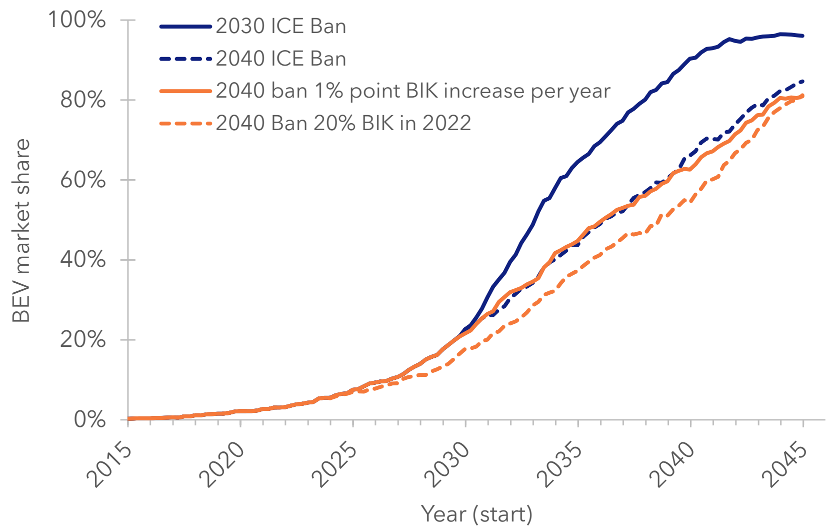


Figure 7.5: Impact of various BIK tax rate schemes on BEV adoption

7.1.3 Company car tax rates

Since fleet purchases represent some 50-60% of new car purchases in the UK, tax applied to these can be expected to have a significant impact on purchase decisions and fleet composition. The base model assumes that BIK rates already announced by the Government remain in place, namely 0% in 2019/20, 1% in 2020/21 and 2% rate from April 2022. Since it seems unlikely that policy would reduce BIK rates again, the scenarios analysed here illustrate the effect of increased rates. Figure 7.5 shows two alternative scenarios, one where BIK rates are immediately increased to 20% in 2022 (the rate applied to vehicles emitting 80-84gCO_2e km^{-1} in 2020/21, currently not achieved by any ICE car) and the other where the 2022 2% rate is increased by 1 percentage point each year. The impact of the rapid reduction is clear, with market share 6.5% points lower in 2030. However, the second scenario tracks the base, fixed 2%, market share until 2040, showing that reducing capital costs and increasing range availability in the market are sufficient to counter the increase in BIK rates. This is important from a policy and equity perspective since it indicates that increasing taxes back to conventional car rates can be achieved without compromising adoption rates.

7.1.4 Vehicle excise duty

VED has long been used as a tool to drive the purchase of lower emission vehicles. In Figure 7.6 shows the modelled impact of three VED schemes. In "Ramp Y1 VED", the initial VED paid on new ICE vehicle purchase is doubled each year from 2020, whilst in "Ramp all VED", both the year one tax rate and future years' rates are doubled. The final scenario delays the increase in annual ICE VED rates until 2030. Whilst doubling may sound drastic, in practice this magnitude is needed to raise the VED rates to appreciably high values in a short space of time. The chart suggests that VED rates have little impact on purchasing decisions, however, this is likely to be a feature of the way in which non-company car purchase decisions are made. Most such purchases are not 'deliberation' purchases, meaning that buyers do not carry out a TCO evaluation. Instead, buyers filter the initial options to all cars considered affordable and with adequate range and then choose a car based on needs such as preferred range, similarity to peers, performance etc. (see Section 3.8.3 and Table 3.10). This means that even if a car attracts a VED of £10,000, provided that is affordable to the user, then they can consider it in their evaluation which may not then weight cost sufficiently over other parameters to prevent its purchase. This may be considered a deficiency in the parameterisation of the model rather than the underlying functionality since tax is specified as a distinct purchase criteria. However, no data could be found to enable specific weighting of this element and, whilst it is included with a weighting for the individual's existence need (i.e. relative affordability), it is not included in peer comparison as a social need. The results are, of course, potentially reflective of real outcomes, but there is also evidence [192] that individuals perceive tax changes that affect everyone equally as having a greater effect on them personally; this would tend to explain why car owners might, in real life, wish to avoid paying the tax by seeking out a BEV instead even if the relative cost benefits are not significant (due to higher BEV cost in early years) or if, for example, the agent's range weighting would indicate a preference for a highly taxed ICE car.

Figure 7.7 shows the impact on company car purchases, where TCO is always taken into account. This clearly shows that VED is having an impact where this kind of evaluation is practiced, with 95% market saturation reached up to 5 years earlier.

7.1.5 Consumer 'greeness'

Whilst it is debatable as to whether the level of environmental consciousness within the population is a direct function of policy, there are clearly opportuni-

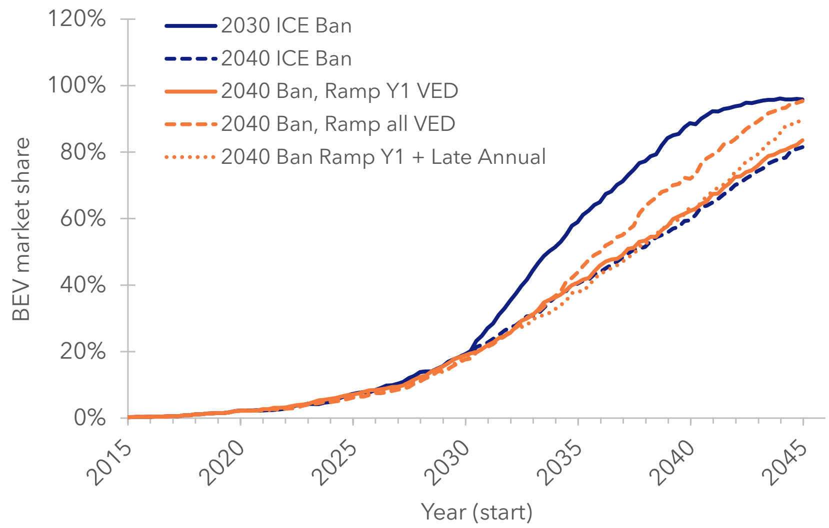


Figure 7.6: Impact of various VED schemes on overall BEV adoption

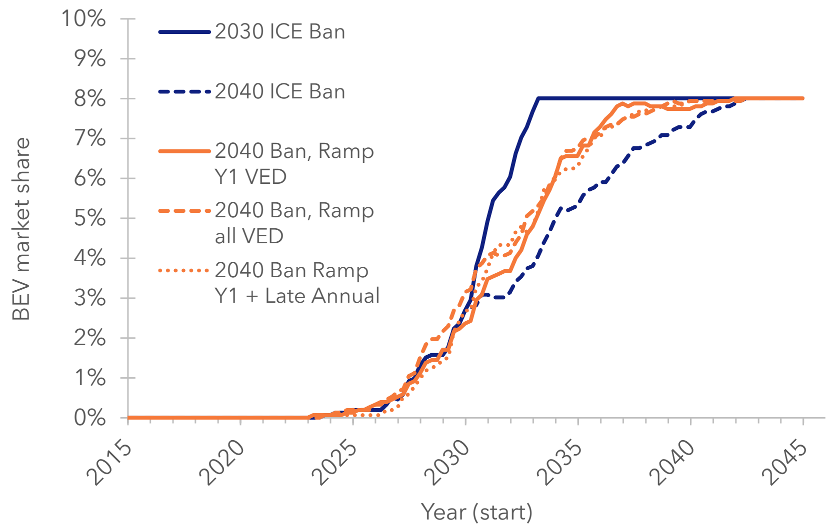


Figure 7.7: Impact of various VED schemes on company car BEV adoption. (Note that approximately 8% of cars on the road are company/fleet cars at any one time, although they represent over 50% of new car purchases [199].)

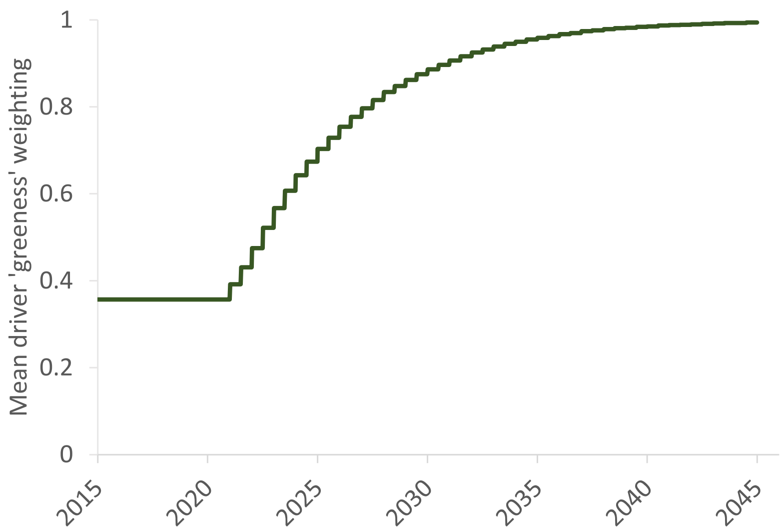


Figure 7.8: Mean greeness index of population over time with bi-annual 10% increase in each agent's greeness index applied.

ties for government's to raise public awareness and the implementation of low carbon policies in general are likely to have such an impact. Thus it seems reasonable to explore the effects of increasing the 'greeness' of the car-buying agents. The model assumes a greeness limit of 0.7 for all agents. To test the impact of increasing greeness, each agent's greeness is increased biannually by 10% from 2020. The effect on the mean greeness of the population is shown in Figure 7.8 and the model outcome (this time compared to a 2030 ban scenario) is illustrated in Figure 7.8. This outcome is somewhat unexpected; i.e. an increase in greeness appears to have even a slightly negative impact on adoption. However, this can be explained since environmental performance is addressed in social needs, with a comparison to peers, and personal needs, with a comparison to media data being the modal average of emissions. Since most drivers are 'imitating' when purchasing a car, provided they have a similar satisfaction level in regard to greeness as their peers, then they will be happy with a less 'green' car. By moving all drivers ultimately to the same level of greeness, they are less likely to seek a lower emission car; i.e. the Status Quo is more acceptable.

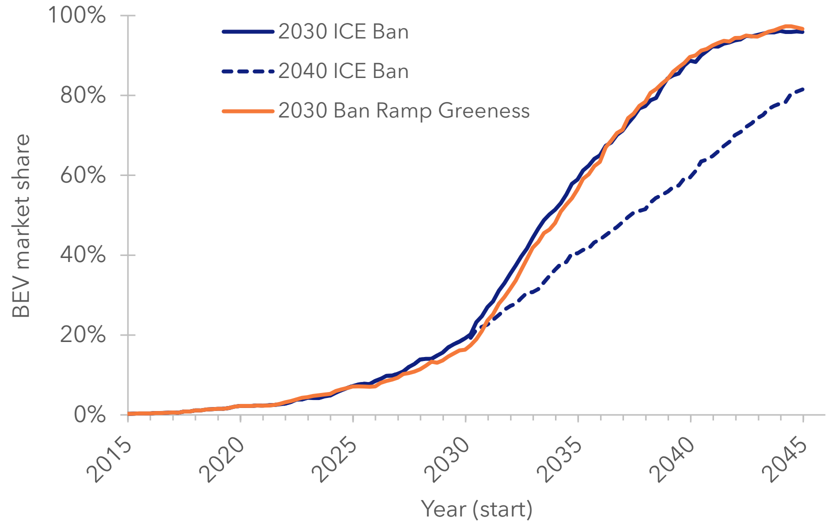


Figure 7.9: Impact of general increase in greeness of the population compared to 2030 ban as base.

7.2 What are the social equity implications of the suggested policies?

In this section, the implications of the various policies outlined in the previous section on social equity are explored. The NTS includes a form of socioeconomic classification, but this includes a geographic component as defined by the ONS. Because of this overlap, there is not always a clear relationship between income and classification. In Figure 7.10 the breakdown of household incomes, by income quintile, for each of the NTS area classifications is presented. The income quintile boundaries were sourced from [230] and comprise 5 groups each with equal numbers of earners. From this analysis it can be seen that whilst there are clear trends, for example, *Suburbanites* have higher incomes than *Constrained City* dwellers, some apparently lower socioeconomic classifications, such as the *Hard Pressed*, also contain some high income households. Thus whilst geographic interpretation can be applied to some classifications, more caution is required when considering economic status as a function of classification. To ensure a more robust analysis, the results are presented disaggregated by income quintile rather than NTS socioeconomic group. However, since the sample employed in the study contains only car-owning households, the quintiles do not represent equal

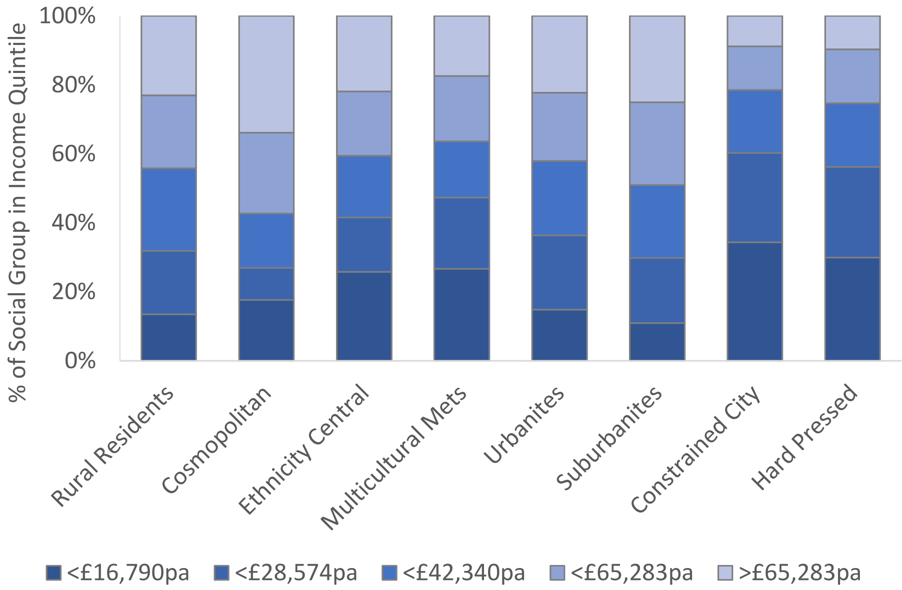


Figure 7.10: Analysis of income within NTS socioeconomic groups

20% populations; Figure 7.11 shows the proportion of car-owners that belong to households within each income quintile in the sample population. Quintiles are numbered from 1 to 5 with 1 being the lowest income and 5 the highest in all charts.

The results are presented as a 4-year rolling average operating cost index relative to January 2020. The operating cost includes road tax, fuel/electricity and maintenance costs. This approach was adopted because quintile groups also tend to have different ownership models; higher income groups are more likely to have a company car or to have a leased car; in these cases, operating costs are lower or encompassed in other costs, such as tax allowances, which are not included in the analysed cost. The index approach provides a relative comparison for each group to a base with very low EV ownership. In this initial analysis, all car charging is assumed to occur at only 2 prices; either the 'uncontrolled' home tariff or the en-route rapid charger rate. A more refined pricing approach is included in Section 7.5.

The lowest income quintile tends to exhibit much greater volatility than other quintiles; this is in part due to a lower number of car owners resulting in less averaging effect, but also because this group owns older cars which are more susceptible to occasional high cost maintenance events.

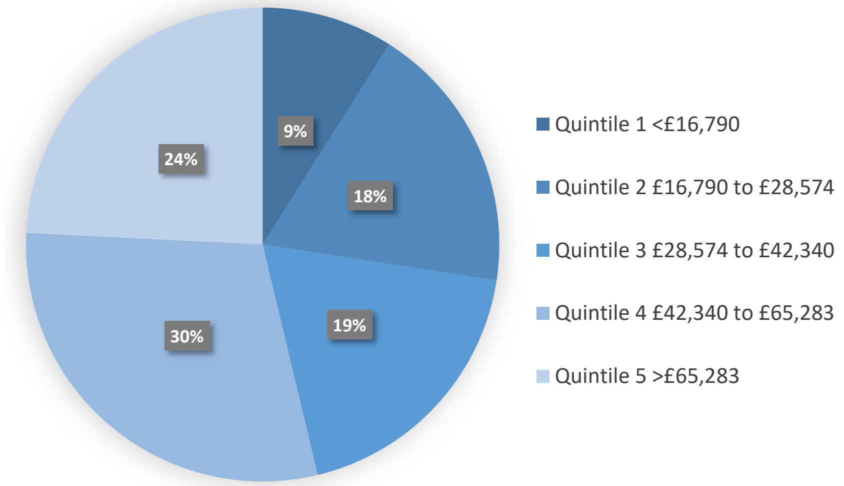


Figure 7.11: Proportions of car owner population belonging to each household income quintile.

7.2.1 ICE vehicle sales bans

Figure 7.12 shows the relative impacts of a 2040 ICE ban and 2030 ICE ban. It can be seen here that the highest income quintile benefits earliest from the introduction of BEVs, regardless of bans, since they are able to afford these vehicles, or may have access to them via company fleets. However, quintile 1 quickly gains from the early ban after 2030; this appears to be the result of used BEVs at costs comparable to ICE vehicles appearing in the market rather than the introduction of the ban itself. That is, the rapid kick in adoption bought about by a 2030 ban causes a cascade of used cars to appear relatively quickly. Quintile 1 drivers are keen to obtain the lower operating costs available from BEVs compared to quintile 3 who may weigh non-financial factors more heavily and thus see an earlier and more pronounced fall in costs. Thus the earlier ban, perhaps perversely given the potential to proclaim the high cost of EVs as problematic, appears to offer a social-equity benefit over a later ban. This does however, need to be considered in the light of company car tax policy; one of the drivers of early fleet adoption which aids in the availability of used BEVs.

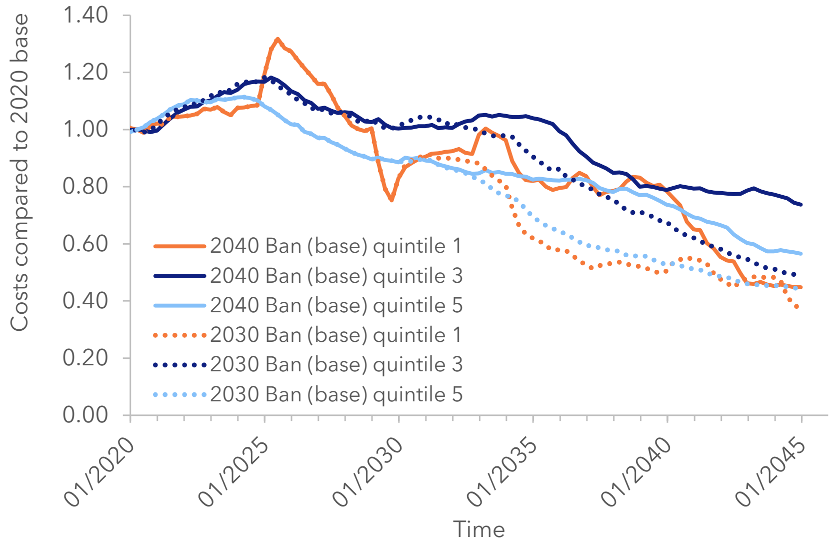


Figure 7.12: Impacts of ICE bans on income quintile group costs

7.2.2 Scrappage schemes

Since the ’£6k all-car’ scrappage scheme, where those scrapping a vehicle over 8 years old can purchase any new or used EV after 2020, was most effective, only that option is considered here. Figure 7.13 illustrates the results from this analysis; quintile 1 groups gain an earlier advantage than with the 2030 ban, and maintain similar cost reductions to the earlier ban throughout. It is notable that it removes the early spike in costs, this is likely to be because car owners had replaced unreliable, expensive to maintain, cars with BEVs under the scrappage scheme. The benefit to high income quintile 5, whilst starting a little earlier, is less than the 2030 ban case and this is almost certainly due to fewer such households having a suitably old car to trade in. Whilst protections could be imposed (such as a minimum period of ownership), perverse outcomes are possible, such as buying an old car only to enable a trade in after the minimum period.

7.2.3 Company car tax rates

Whilst other changes to company car tax do have some impact on quintile costs, the major difference in adoption was observed with the rapid increase to 20% BIK rates, the effect of this option is illustrated in Figure 7.14. (The base case assumes BIK rates remain at 2%) The costs experienced by higher earners remain fairly sim-

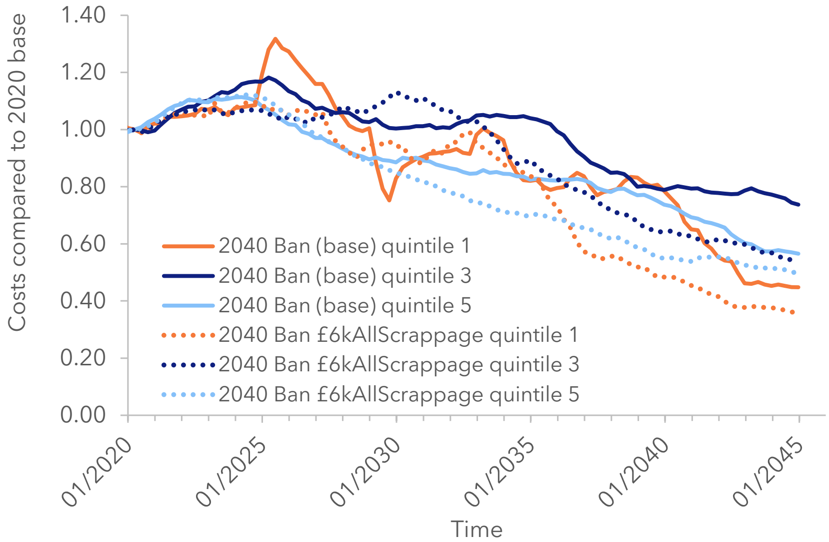


Figure 7.13: Impacts of £6k all-car scrappage scheme on income quintile group costs

ilar; this is because tax costs (other than VED) are not included in the operational cost analysis. There are greater swings for the lowest quintile group, partly due to lower numbers, but the increase around 2035-39 arises from a greater number of ICE vehicles, rather than BEVs, being available in the second hand market. Thus it can be concluded that company car tax benefits do cascade through to benefits for lower income groups, though this is also achieved when BIK rates are ramped back to ICE-type levels and this option also helps preserve tax revenues.

7.2.4 Vehicle excise duty

Figures 7.15 and 7.16 illustrate two of the VED options with dramatically different outcomes in regard to quintile costs. In the 'All VED ramp' scenario (Figure 7.15) quintile 3, and to a lesser extent quintile 5, see their costs rise inexorably until just prior to the 2040 ban. This is because those drivers can afford the additional cost of the VED in the early years and since their peers also experience a gradual increase in costs, the variance they experience will remain low (both in costs and car type/fuel). Quintile 5 drivers are more likely to have sufficient income to purchase a high-specification EV early thus their costs do not rise so quickly, a greater proportion having invested in BEVs. Quintile 1 drivers cannot afford the additional costs and move more quickly to BEV ownership, this has the side effect

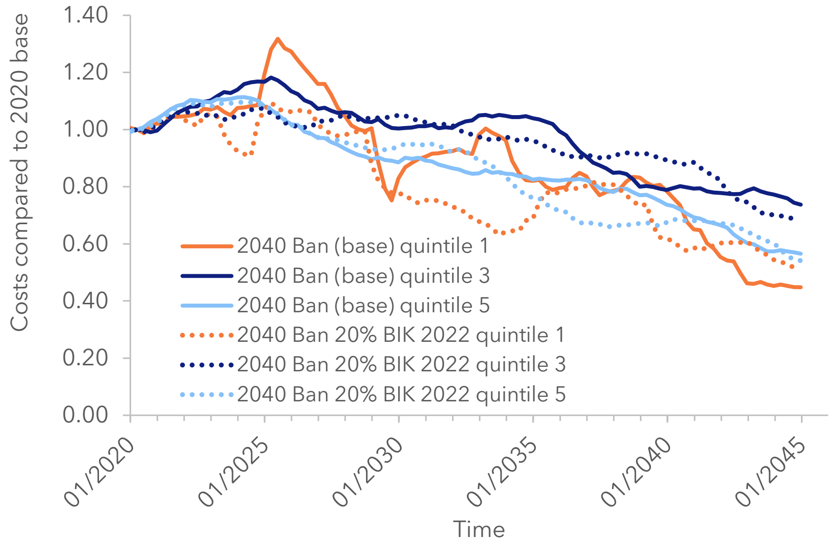


Figure 7.14: Impacts of 20% BIK rate introduction on BEVs on income quintile group costs

of fewer used BEVs being available for the middle income groups to purchase. Overall, this option leads to the most rapid and sustained decline in costs for the lowest income group. Switching to a later increase in the annual VED rate (Figure 7.15) delivers fairly flat costs for the middle-income quintile, but the costs for the lower income quintile are similar to those for the 2040 ban case.

7.3 How do these policies impact on carbon emissions?

Figure 7.17 illustrates the impact of the policies examined in the previous section on mean fleet CO_2(e) emissions. This analysis includes notional figures for embodied carbon in the battery and glider (see Section 3.11.2) and contrary to Brand et al. [29], indicates that scrappage schemes do have a positive impact on emissions; this is likely due to the fall in grid emissions since their study. As would be expected, any policies that reduce adoption rates lead to a lower reduction in CO_2 emissions. However, these results also indicate that fleet zero emissions may not be reached by 2050 without action to remove remaining ICE vehicles. One consideration not included in the model that may lead to a greater adoption of EVs in later years, i.e. to force 'laggards' into adoption, is the reduction in availability of conventional fuels as filling stations becomes less profitable. The scrappage

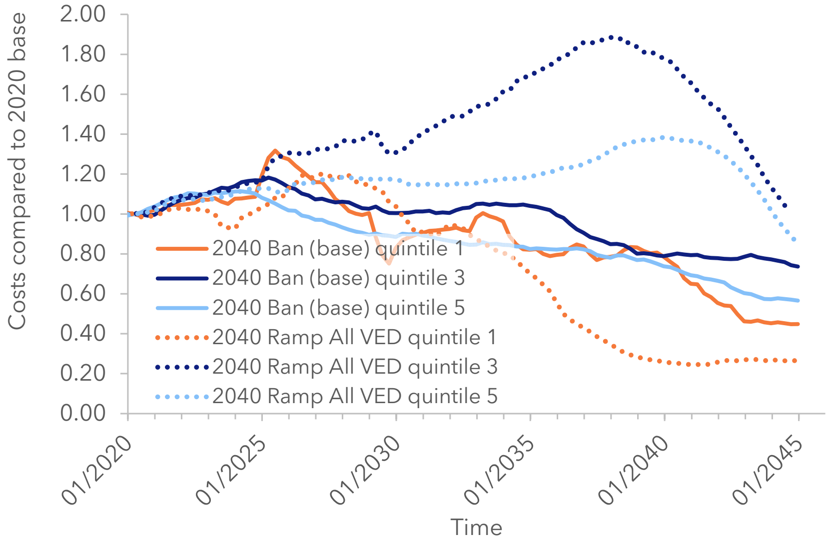


Figure 7.15: Impacts of increasing year one and annual VED rates from 2021 on income quintile operating costs

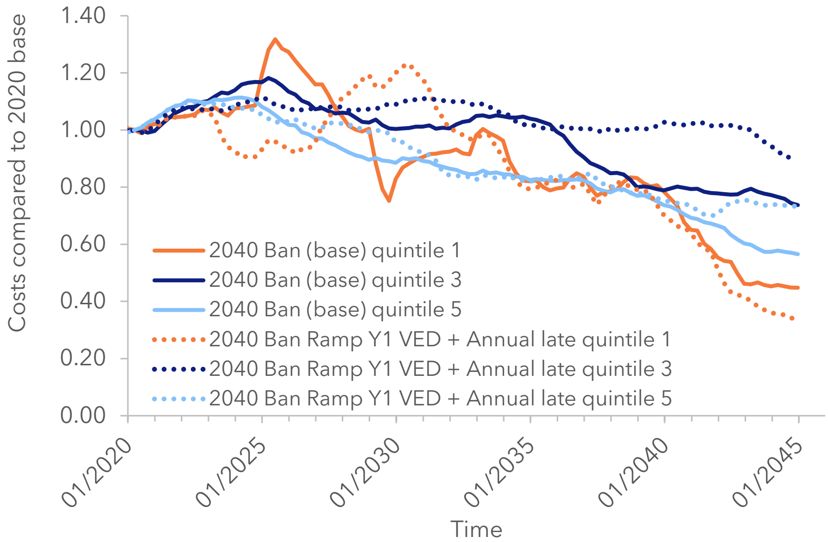


Figure 7.16: Impacts of increasing year one and late (2026 start - at BEV cost parity) annual VED rates on income quintile operating costs

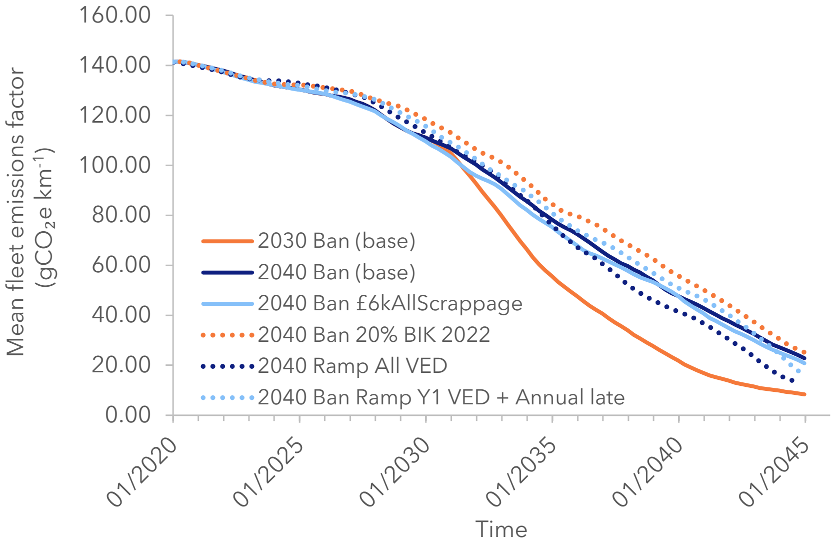


Figure 7.17: Impacts of various policies on fleet average CO_2e emissions

scheme, which is the only policy directly targeting vehicle emissions, results in a only marginal benefits compared to alternative policies.

7.4 Charging infrastructure

Whilst the installation of chargers may be considered the role of the private sector, as it is with ICE vehicles, there is recognition that a 'chicken and egg' situation exists; the economic case for installing chargers when there are few users is poor, but consumers will be reluctant to purchase BEVs until the charging infrastructure is in place. As such, many government's have supported the roll-out of charging infrastructure; in the UK, various grant schemes have been in operation since 2016, covering home, workplace, local authority and rapid charging provision [216, 217]. Whilst it is difficult to directly link these funds to numbers of chargers installed (since costs are highly variable and there are many installations which have not received grant funding), it is reasonable to consider the availability of public charging provision, particularly in locations with fewer potential users, to be a function of government policy.

Figure 7.18 illustrates the roll out of destination chargers at the the three different location types where facilities are included in the simulation for both the early deployment case (used for previous analysis) and the more realistic deployment scenario. Figure 7.19 shows the impact of these two rates on BEV deployment with a 2030 ban and 2040 ban. In the case of the 2040 ban, only destination chargers (as per Figure 7.18) are deployed late, whereas in the 2030 ban, rapid charger installations proceed at 5% per annum after 2018 rather than 10% as in the base case. Referring to Figure 3.6, the installed base of en-route rapid chargers is already significant and whilst more are required to ensure waiting times do not increase as adoption increases, the current separation distance is adequate to ensure that drivers will not get stranded in normal circumstances. Whilst waiting for a charger does incur a range satisfaction penalty in the model, this is only related to the time of charging (hour of day) and not to the ratio of rapid chargers to BEV ownership, thus reducing future installation rate has little impact on adoption, illustrated by the similar adoption curves prior to 2030 for both late infrastructure scenarios. It should also be noted that the absolute number of chargers is not the metric used by car owners to evaluate range requirements, rather it is their knowledge of charging provision, which is effected by both the number of chargers 'seen' at locations visited and the number of peers owning BEVs, thus a relatively small change in charging provision, which affects the number of early adopters, can have a significant impact on mean charging knowledge and overall uptake. The accuracy of this strategy is unclear and this is a part of the model that would benefit from further survey work and parameterisation.

7.5 A postulated policy approach

The analysis above gives a good indication of the effectiveness of a number of policies for which there is some historic precedent. A fuel duty escalator is another possibility, but history has shown that it is difficult for Government's to maintain commitment to this under lobbying pressure and adjustments are often needed to take account of swings in the underlying crude oil price. The simulation employs historic oil prices (over 30 years) with current duties applied, thus modifying duties does not give a direct correlation between fuel price and adoption. It is also probable that as fuel duty receipts fall, the Government will need to introduce a new means to raise tax revenue from motorists, indeed, there has already been a call for evidence on this subject [218], looking at road pricing mechanisms that would apply to both ICE vehicles and BEVs. Assuming this is adopted at some stage, then the existing fuel duties might continue to be applied as a further disincentive to continue driving fossil fuel vehicles, whilst road pricing might be applied equally to all vehicle types.

The Government has already indicated its intention to introduce a phased ban,

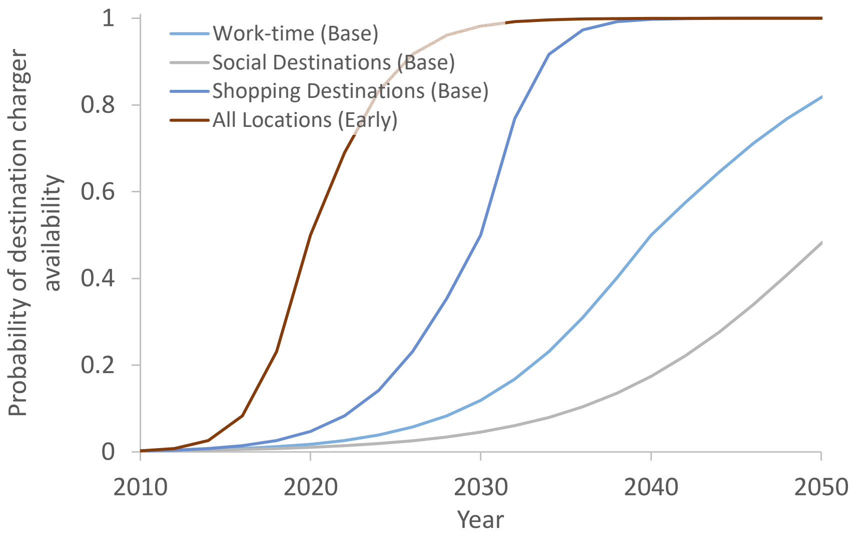


Figure 7.18: Early (unconstrained), used in policy analysis and base case (for postulated policies) charger installation curves

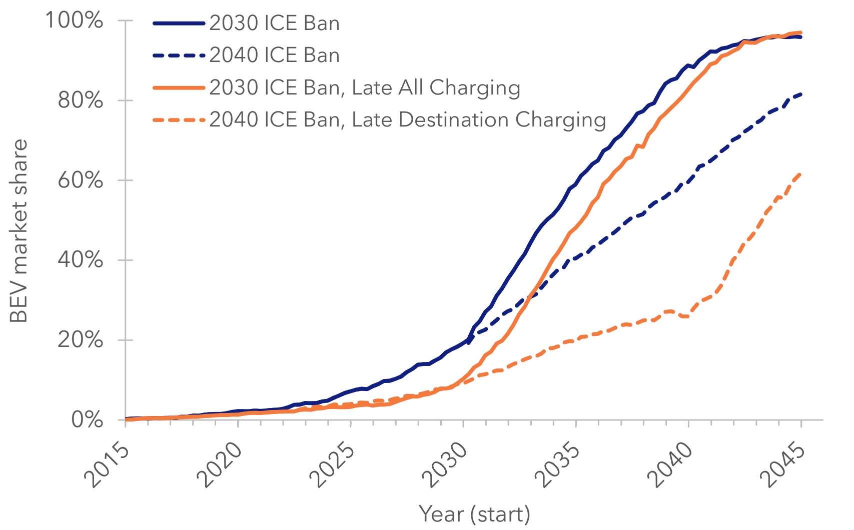


Figure 7.19: Impact of early (does not constrain growth) and postulated realistic installation of charging infrastructure

with pure ICE vehicles banned from sale in 2030 and hybrids from 2035 and this approach certainly appears to be the only route with the potential to deliver a zero emission fleet by 2050. Company car tax policy is an important element in driving new BEV sales and the analysis here indicates that a slow increment in BIK will not impede adoption and will help balance tax revenues from that source. The impacts of increasing VED on ICE vehicles appear relatively small compared to the benefits delivered from direct bans, which do not themselves incur any tax revenue penalty to the Government (indeed they may increase tax revenues due to higher VAT receipts on, initially, more expensive EVs). It therefore seems likely that existing tax exemptions on EVs will need to be wound back as price parity approaches in order to preserve those tax revenues. To explore the impacts of more realistic overall policies, the tax regimes illustrated in Figures 7.20 and 7.21 are applied. These are designed to replicate current non-fuel taxes from 'average' ICE vehicles, whilst ensuring a benefit always exists for BEV owners and avoiding highly penalising taxes for those unable to afford a BEV until sufficient vehicles are available in the used market. The more conservative charger roll-out provision is also modelled and home charging is adjusted to occur during off-peak periods at 6p kWh^{-1} unless immediate charging is required to complete the next journey, in which case charging starts at the standard rate of 14p kWh^{-1}. All destination charging, including that for those without home chargers, is costed at 25p kWh^{-1}.

Figure 7.22 illustrates the market share of BEVs resulting from the postulated policies and charger installation rate compared to the previous base case. This chart also plots the impact on PHV adoption, showing that there is an increase in PHV adoption under the proposed 2035 ban. However, the increase is not significant, which is largely a result of the cost reductions and range increases modelled for BEVs, which render PHVs unnecessary, and more costly, than pure BEV alternatives.

Figure 7.23 illustrates the effect of these postulated policies on the income quintiles presented in the previous analysis. This shows quintiles 3 and 5 achieving fairly consistent cost reductions, but much more erratic behaviour for quintile 1. This appears to be caused by occasional high maintenance costs and the small number of car owners in this quintile. A further complication here is that it is possible for agents to exist without a car for extended periods in the model. This can happen if a car owner disposes of their current car because costs exceed the maximum allowable under their 'existence need' requirement and cannot immediately obtain a suitable replacement. In this analysis there are, on average, 6.1% of drivers without cars at any given time from 2020 to 2040 compared to 4.1% in the 2040 ban base case. However, by the simulation completion in 2045, the number

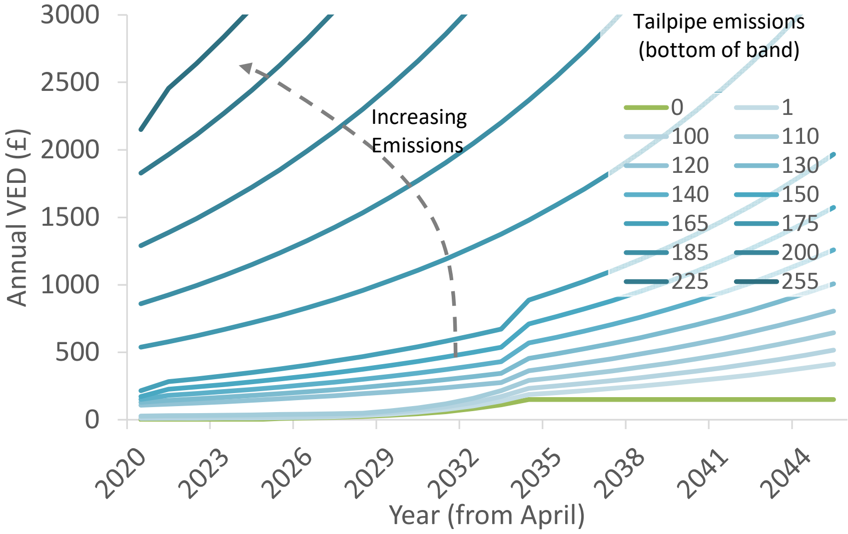


Figure 7.20: Postulated year 1 VED policy; BEV rate is always maintained below the lowest emission ICE car rate, annual rates are capped at £5000.

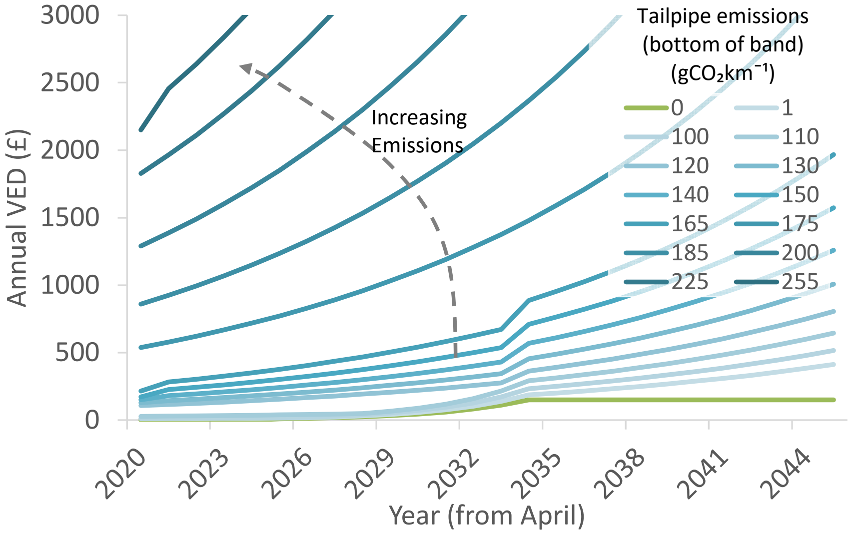


Figure 7.21: Postulated annual VED and BEV BIK rate. These are designed to reach similar values to those currently applied to 'average' ICE cars.

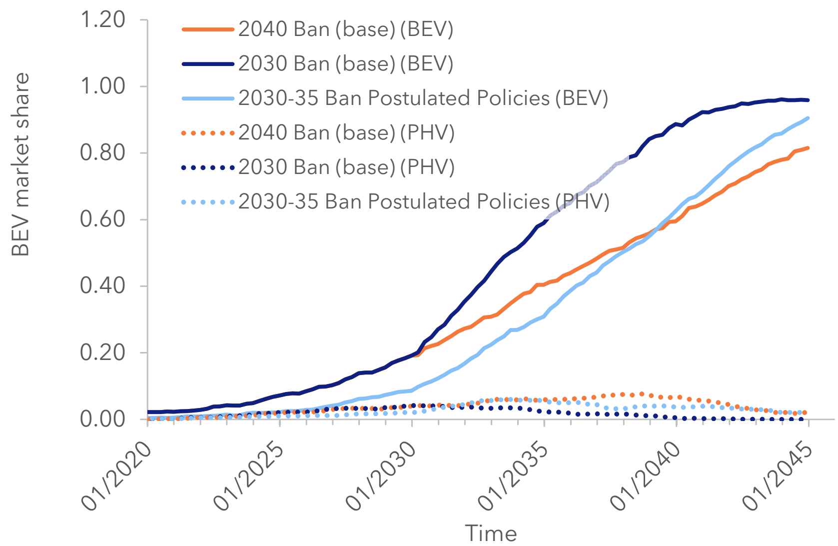


Figure 7.22: Adoption of BEVs and PHVs based on postulated tax environment and charger deployment.

of owners without cars has fallen to 3.2% in the postulated policy scenario whilst remaining close to the long term average at 4.7% in the 2040 ban case. Whilst it is not possible to obtain the breakdown by quintile from the data available, it seems plausible that the lowest income groups would be disproportionately affected by the availability of suitable, affordable, electric cars, but once a wide range of used cars are available, the lower operating costs allow for greater choice for low income groups.

Figure 7.24 shows how providing home charging for all car owners (perhaps through on-street charging points) at the same cost as home charging affects operating costs. This does not produce such an obvious benefit as one might expect; quintile 1 appear to experience much higher costs as a result. Whilst quintile 3 do exhibit lower costs, quintile 5 drivers seem to experience a period of higher costs before falling lower. This apparent anomaly may be a sign of instability in the model, with minor differences in vehicle availability and adoption having disproportionate impact on, particularly, quintile 1. Whilst not shown here, quintile 2 also shows a minor increase in costs, whilst quintile 4 shows a reduction similar to quintile 3. However, this may be a reflection of the 'market' dealing with insufficient supply of used EVs. If higher income quintiles, such as 3 and 4, make a choice to purchase a BEV earlier because range constraints are reduced

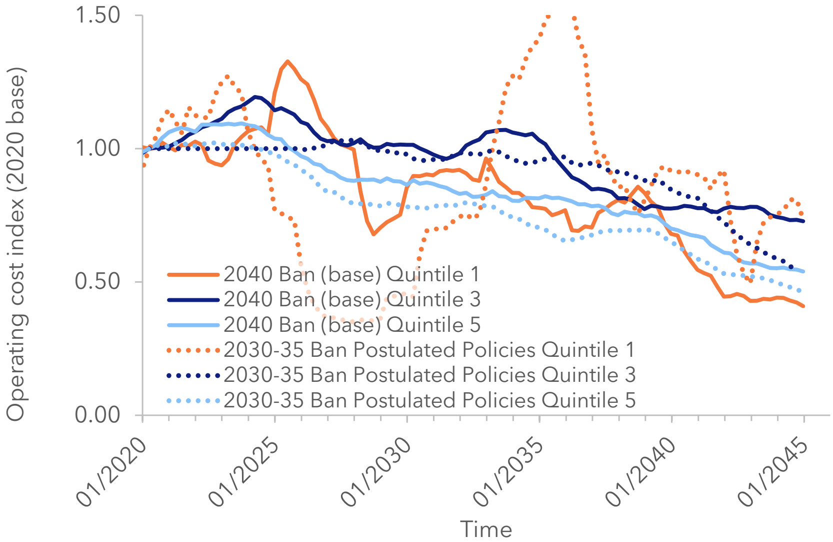


Figure 7.23: Cost index for Income quintiles 1,3, and 5 under postulated policies

through the availability of home charging, then there will initially be fewer lower cost BEVs available to lower income groups. Since the homophily index ensures greater connection between groups of similar income levels (both actual income and indirectly by social group and location), this may reduce the rate of adoption amongst those groups, meaning that they retain older ICE cars for longer and suffer higher maintenance costs as a result. The reason why the highest income quintile costs do not show a reduction are unclear, although it may be that higher income groups tend to drive more and may use more remote (rapid or fast public) charging on long journeys. Thus the higher income groups who do not have home charging in the base postulated model adopt earlier because home charging access reduces their perceived range requirement, but then end up spending more because they do more remote rapid charging than low income groups.

It is also important to consider the relative impacts of maintenance and energy costs on total costs. Table 7.1 sets out the modelled costs for a 'C' Segment petrol car and BEV car, when new and at 8 years old, for home charging (assuming all ToU tariff) and public charging (not rapid charging). Tax is excluded since this varies depending on the year in the simulation. Given that low income drivers are unlikely to own a new car, this table shows that the fuel element of their cost is a much smaller proportion of overall operating costs. Furthermore, since low income drivers also tend to drive fewer miles, this fraction will, on average, be

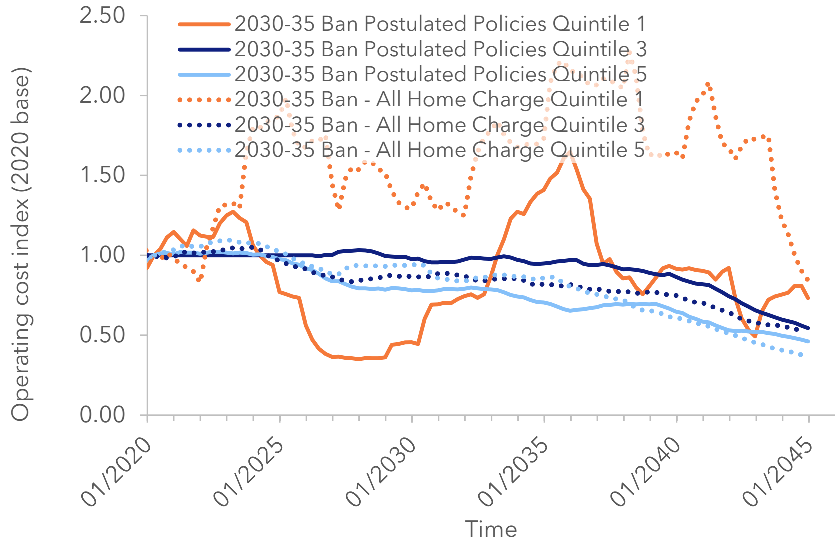


Figure 7.24: Cost index for Income quintiles 1,3, and 5 under postulated policies and scenario where all users have access to home charging

even smaller than shown here. Thus maintenance costs are likely to dominate the costs experienced by these owners, particularly when home charging is available. However, the percentage cost reduction experienced by home chargers compared to public chargers is significant; in the table (final column), new BEV costs are compared to new petrol car costs and likewise for 8 year old cars.

Table 7.1: Operating cost analysis (excluding tax & insurance) for 'C' Segment petrol and BEV cars at average UK mileage (11,850km)

Car option	Annual Maint. £	Annual fuel £	Cost per km p km^{-1}	Fuel Fraction %	Reduction %
New petrol car (£1.20 $litre^{-1}$)	220.00	716.00	7.91	76%	-
8 year old petrol car (£1.20 $litre^{-1}$)	543.40	716.00	10.64	57%	-
New BEV - Home Charge (6p kWh^{-1})	130.00	124.63	2.15	49%	73%
8 year old BEV - Home Charge (6p kWh^{-1})	321.10	124.63	3.76	28%	65%
New BEV - Public Charge (25p kWh^{-1})	130.00	519.30	5.48	80%	31%
8 year old BEV - Public Charge (25p kWh^{-1})	321.10	519.30	7.10	62%	33%

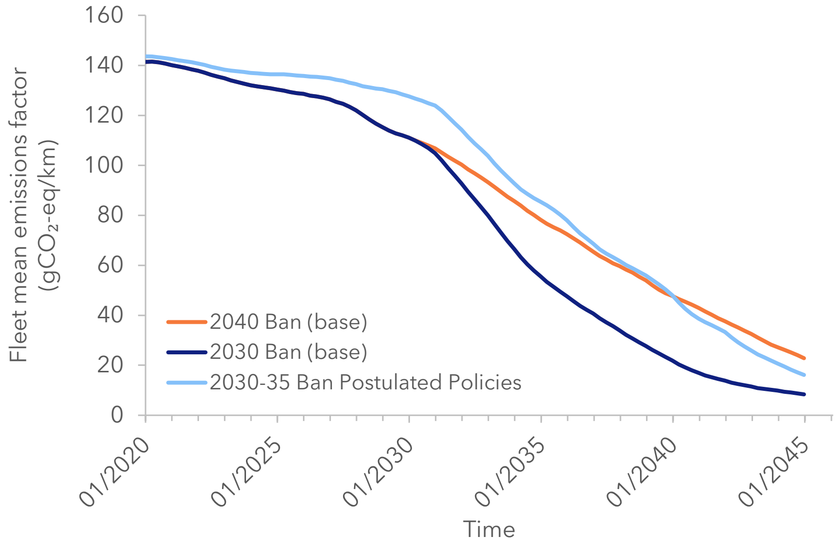


Figure 7.25: Impact of postulated policies on CO_2e emissions

7.5.1 Impact of postulated policies on carbon emissions

Figure 7.25 compares the average fleet CO_2e emissions under the set of postulated policies with complete ICE bans in 2030 and 2040. The delayed reduction in emissions is primarily a result of charging infrastructure availability and its impact on range requirements and vehicle choice. The model does not predict a high take-up of hybrid vehicles between 2030 and 2035, so there is no obvious effect from this delay in the ban.

7.6 Conclusions and further discussion

7.6.1 Model caution

The model is not fully parameterised with regard to weighting of the satisfaction measures and the decision process on range requirement is also somewhat speculative, though the outcome in regard to desired range is supported by the literature. The effect of policies that impact most directly on TCO for fleet purchasers can be considered relatively robust and this does have a significant impact on BEV adoption. Other areas, such as charging provision and impact of taxes on non-fleet buyers should be considered as more speculative. The impacts of some measures can be rather difficult to observe in the data. This may be the result of complex interactions in the early stages of adoption when a few individuals in one demographic adopting early, by virtue of the homophily index, may result in a large increase in adoption across that group or vice-versa. This is a feature of real-world interactions, but will be influenced by the number of agents in the model and their degree of interconnection, which is empirically based rather than sourced from robust survey data. As such, what is largely of interest here is the relative effects of policies rather than absolute numbers.

7.6.2 Policy choices: which policies are most effective and how can they be tailored to maximise social equity?

The modelling shows that direct sales bans are the most effective at accelerating adoption. These also offer the benefit that there is little direct cost to Government. Perhaps more surprisingly, such bans also deliver social equity benefits in that they ultimately deliver lower costs to low income groups earlier. It is also apparent that company car benefits can be withdrawn over a reasonable time-frame without impacting adoption. Whilst this may be predicated on reducing capital costs, it is clear that this is happening today and TCO calculations can already yield benefits for high mileage drivers. Timing the withdrawal of these benefits, together with road tax exemption, such that deployment is maintained as costs reduce can also help to deliver a more equitable transition by reducing the tax subsidy available to these, generally more wealthy, drivers. More direct support to less wealthy drivers might be provided through a scrappage scheme, but to be effective this would have to include support for the purchase of used BEVs. If this policy were to, somehow, be targeted only at the lowest income quintile group, then the costs of such a policy could be as high as £17Billion, some 16% of total UK tax revenues in the 2020-21 tax year [109]. This is clearly an implausible sum of money and thus any scheme would have to be limited, further reducing its social equity benefit. Any such scheme, and its funding source, would need to be very carefully designed to avoid perverse outcomes or inflicting a greater tax burden on the less wealthy.

7.6.3 Charging provision

The availability of charging provision, though not necessarily home charging, has a notable impact on adoption and is therefore rightly the object of current government support. There are undoubtedly complex interactions here with both the types (rapid/standard) and locations of chargers being important. Furthermore, charging represents a new and poorly understood element of BEV ownership. A short perusal of BEV social media groups immediately reveals confusion, and occasionally, despair, at the complexity of BEV recharging compared to refilling a car with petrol (see box). Existing charging installations are also often unsuited to their locations; customer dwell-time ought to dictate the charging speed, yet capital cost and grid availability appear to be equal determinants in many locations. Thus the existing installed base of chargers may not meet the needs of BEV drivers. Whilst the method used to ascribe charging knowledge and influence consumer choice in the simulation is novel, and more detailed than previous attempts, it cannot encompass the the wide range of situations, issues and peer feedback that may occur in the real world.

Example Social Media Post (11/07/2021)
"Help!!! Stuck at services. 1st run out with new car. To be honest charging all weekend been a nightmare. On way back to Sheffield with 2 young crying kids in car. Trying and failing for over 50 mins to connect. Kicks me out every time. What am I doing wrong. DM for help? Happy to take a call from any experts"

The actual number of rapid chargers is also increasing at a rate faster than the model prediction of 10% per annum, with a 38% increase in generic CCS [241] (i.e. suitable for Tesla and all other manufacturers) between the original modelled data set at the end of 2019 and the end of 2020. (Standard 7kW chargers increased by 14%, but there is no location breakdown to match to the modelled forecast.) It appears likely that charging provision will keep up with EV deployment and is more likely to represent a perceived, rather than true, barrier to adoption. The positive effect of better consumer knowledge is evident from increasing BEV advertising in the model; it is perhaps equally important for charging services to advertise their presence as the car manufacturers themselves. However, as yet there appear to have been few, if any, EV charging media campaigns directed at the general public in the UK, although direct advertising via social media, presumably largely to existing BEV owners, does occur. A government programme aimed at improving consumer knowledge regarding EV charging and awareness of infrastructure, may be a prudent element in avoiding negative feedback from the "early majority" (Figure 2.2) , who are likely less informed and less tolerant of the challenges compared to "early adopters".

7.6.4 Fleet carbon emissions

In essence, the fleet carbon emissions are directly linked to BEV adoption rates. The modelled outcomes indicate that delaying the ban on hybrid vehicles does not have a significant impact on carbon emissions since by 2030 BEVs are price and range competitive with both PHVs and HEVs and there is only a minor increase in sales of such cars compared to an outright 2030 ban. It is also notable that the most effective scrappage scheme modelled has little impact on emissions, an impact that may be further reduced by improved efficiencies in ICE vehicles between now and the bans being imposed. Only outright bans appear to offer the prospect of achieving zero emissions from private vehicles by 2050.

7.6.5 Likely policies and impacts

The set of postulated policies appear to offer a reasonable compromise on adoption at little social equity cost provided that charging infrastructure deployment continues apace and the public are aware of this provision and the range capabilities of BEVs. Figure 7.26 compares the model output for a complete 2030 ban with no infrastructure constraints and improved public knowledge and the postulated policies scenario with the NGC adoption scenarios. This gives good agreement between the most optimistic and less optimistic forecasts. Whilst it suggests that the postulated policies, closest to current Government thinking, will only achieve the lower deployment rates, the additional charging knowledge and public awareness may well see a result between the two. An adoption rate faster than the most optimistic scenarios here is unlikely due to vehicle turn-over rate limits, which may also be constrained by manufacturing capacity.

Ultimately, the impacts on different socioeconomic groups will also be influenced by the policies adopted to replace lost fuel duty and VAT revenues. Assuming the 'postulated policy' scenario presented, by 2035, about one third of all vehicles are BEVs, leading to a loss of fuel duty revenue in the order of £10Billion per year [169]. Replacing this from a mileage tax applied to all car owners suggests a tax rate of approximately 6.8p km^{-1} (4.2p $mile^{-1}$) in 2035. Applying the tax only to BEVs would see a 2035 tax rate of ca. 20p km^{-1}, making BEVs more expensive to run than ICE cars and likely slowing the transition. Any such direct tax on miles driven is, within the bounds of car efficiencies, a direct replacement for existing fuel duty. However, that does not necessarily imply palatability to consumers and there would doubtless be concerns, particularly from *Rural Residents*, over its fairness and the lack of alternative public transport options.

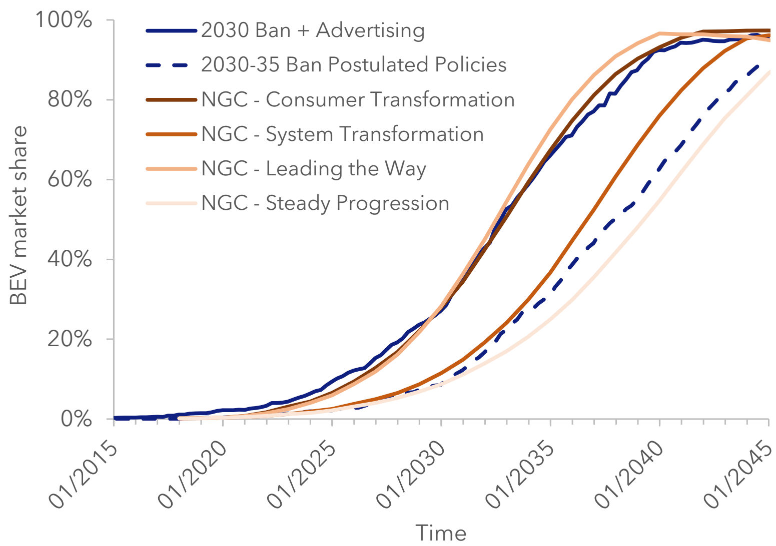


Figure 7.26: Comparison of rapid adoption and postulated policies with NGC scenarios

Chapter 8

BEVI results and discussion - grid impacts and opportunities

In this chapter, the results of a suite of analyses conducted using the BEVI model are presented. The questions to which answers are sought are:

1. What are the impacts of EV charging on local network demands in different areas?
2. What capacity of energy storage may be available to grid operators?
3. How can this capacity be applied in a V2G application?
4. What are the social equity implications of these demand increases?

To answer these questions requires consideration of a further question:

5. What range of battery capacities can be expected in BEVs of the future?

This fifth question is important for several reasons. Most obviously, the size of battery impacts on the capacity available to grid operators. However, it also affects consumer charging strategies and the viability of EVs for those with limited access to charging. Early adopters of EVs often employed an 'ABC' strategy; 'Always Be Charging', and those with home chargers would often charge immediately on return home [77]. However, as battery size and vehicle range has increased, it is no longer necessary to adopt such a strategy since many newer EVs, even today, can comfortably provide a week's average driving (ca.250km [223]) from a single charge. Those without home chargers can also re-charge once a week at a local supermarket for example. Being of importance in establishing answers to questions 1 to 4, the anticipated sizing of EV batteries is addressed first.

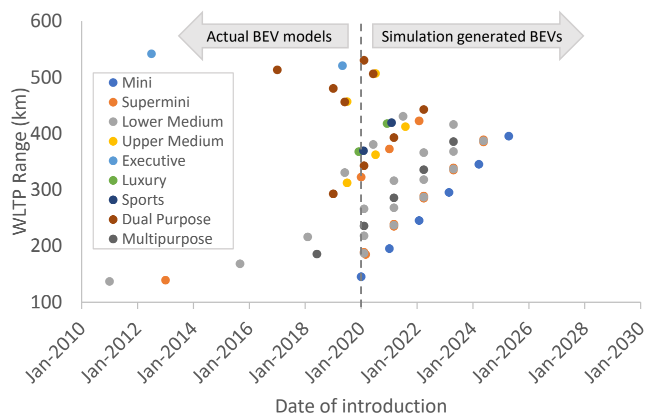


Figure 8.1: BEVs included in simulation, showing model-generated BEVs from 2020, coloured by market segment, and that the need for ranges of over 400km is limited

8.1 EV range evolution and battery capacities

What range of battery capacities can be expected in BEVs of the future?

In this section, the impacts of the simulated 'new model' generation (Section 3.3.2) on the composition of the fleet in regard to range and battery size is explored. The range of EVs generated by the simulation and illustrated here is common to all other analysis in this section.

Figure 8.1 shows the models by market segment that are added to the simulation as time progresses. The most notable feature of this is that the desire for longer range vehicles diminishes over time as more of the car-owning population receive information about charger availability and range satisfaction from peers. Approximately 48% of drivers fall into the 'range-rhetorical' [165] category at the start of the simulation, meaning that they will only be satisfied with cars that achieve a similar range to ICE vehicles (a 600km minimum range and 1000km target range). These drivers only modify their range desires when 60% of their peers are driving BEVs or when the the longest range car available in the market, less than 1 year older than their existing car, has a range of under 1000km. Thus provided that sufficient car owners adopt BEVs at lower ranges, other driver's range ambitions are moderated; the simulation here suggests that is likely to happen.

In Figure 8.2 the BEVs in the 2045 fleet are shown as a histogram by range. Strikingly, nearly 50% of EVs fall into the 350-400km range band. However, it is worth noting that this range is based on WLTP standard cycle; winter ranges will

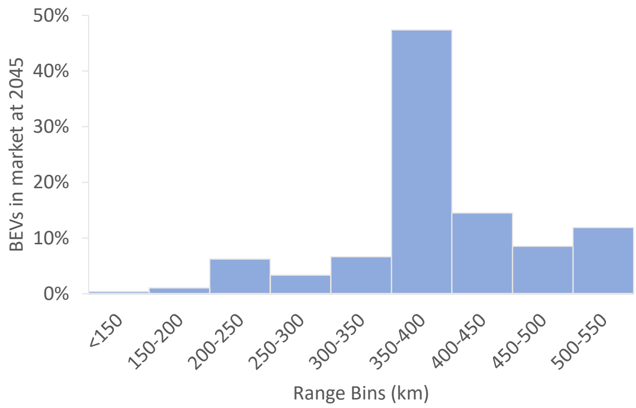


Figure 8.2: Histogram showing percentage of 2045 BEV fleet falling into each 50km range band

be lower and thus drivers may wish to opt for a higher WLTP range than indicated here. Geotab, a fleet management data service, have log data on 4,200EVs over 5.2Million miles and present a curve for real-world EV range performance against ambient temperature [8] as illustrated in Figure 8.3. Thus in fairly extreme UK conditions of -5°, there could be as much as a 30% reduction in WLTP range.

Consumer surveys have tended to show slightly increasing range preferences over time. For example, a 2013 survey from the US [34] indicates that only 40% of EV drivers sought a range of more than 320km, whereas whilst a 2016 survey indicated a similar proportion requiring 305km as a minimum range, some 78% of respondents expected their next car to have a range of over 305km. This later survey also showed large variance in responses from existing Tesla drivers and other EV drivers, with Tesla owners expecting higher ranges. It is unclear why this might be the case, but it could be simply that Tesla have generally had higher range cars and thus expectations are higher or, conversely, that lower than expected winter ranges have driven up the target range desire. It is also notable that these surveys have focused on existing EV drivers; a more general 2020 survey [40] suggests the tipping point for EV purchase is a vehicle with a 282mile/454km vehicle at a price of £24,000 in the UK.

The ranges shown do not correspond to a similarly distributed range of battery sizes as illustrated by Figure 8.4 since the efficiency of the EVs in the model varies and increasingly large batteries also result in lower efficiency (due to increased weight) and thus range per unit of capacity. However there is a clear indication that batteries in the 70-80kWh range would suffice for most drivers, with a signif-

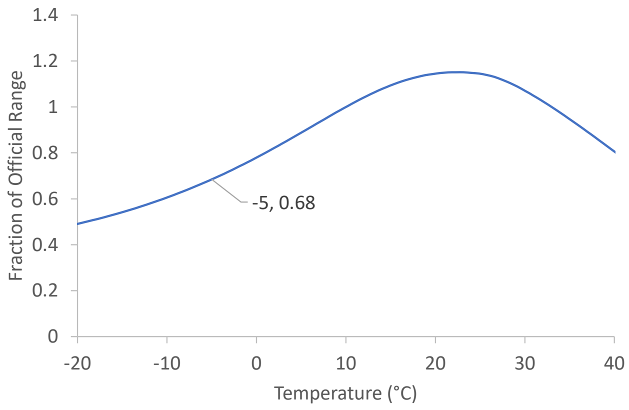


Figure 8.3: Plot of EV range as percentage of official range against ambient temperature from Geotab EV fleet data [8]

icant number happy with lower range and consequently smaller battery. Batteries of less than 40kWh seem unlikely to have any significant market share as EV technology becomes more cost competitive with ICE.

8.2 Localised network demands arising from charging strategies

How will EV adoption impact on demands in different parts of the low voltage network?

In this section, the simulated network demands for four socioeconomic groups with clear geographic boundaries are presented. These are based on the EV growth resulting from the postulated policies set out in Section 7.6.5. Three possible charging strategies are modelled:

- Uncontrolled: charge immediately on return home
- ToU: delay charging until off-peak overnight period
- Controlled: a heuristic algorithm for controlling charge start and stop times that is independent of the grid operator.

The data is extracted from the model from the same, February Wednesday, each year and the time scale is for the end of the year indicated (i.e. the figures effectively extend to the beginning of 2045). A Wednesday was chosen to avoid

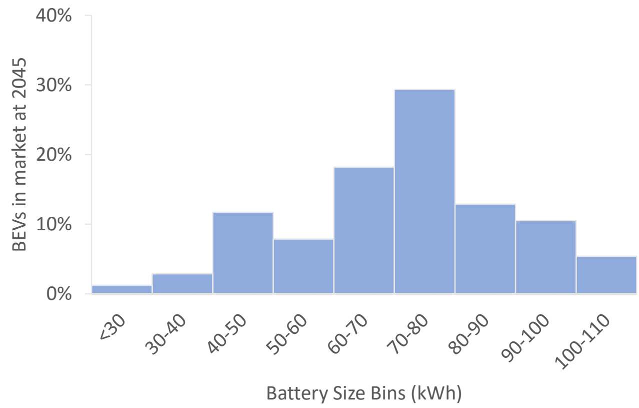


Figure 8.4: Histogram showing percentage of 2045 BEV fleet falling into each 10kWh battery band

weekend effects on ToU demand on a Monday and reduced commuting which can occur later in the week. The simulation does not include any adjustment for ambient temperature, so the time of year is not relevant to the data produced. It will also include randomly generated 'unplanned' journeys that can occasionally produce unusual outcomes, though these are normally disguised by averaging across the groups presented. The simulation sample includes only individuals who owned a car in the NTS 2016 dataset and their associated households (BEV adoption figures therefore represent the fraction of current car owning individuals owning a BEV). However, this is not a relevant comparison for network operators since they are interested in the After Diversity Maximum Demand (ADMD) across a locale, which in this case will include non-car owning households. Thus the social group demand is adjusted by the 'Demand ratio', the ratio of car owning households to all households, shown in Table 8.1

8.2.1 Uncontrolled charging

In this scenario, drivers are assumed to plug-in and charge as soon as practical. The model differentiates between those with home chargers and those without as follows:

Home chargers only charge away from home if they are unable to complete the next journey, plus their individual comfort margin, on their current battery charge.

Table 8.1: Comparison of full 2016 NTS dataset and reduced car-owning dataset employed in simulation with demand ratio applied to household demands for each social group. (hh = housesholds, mean km are weekly)

Ref	Social group	2016 Full dataset			Simulation Sample				Demand
		All hh	Non-car hh	Non-car %	Drivers	Car hh	All hh	Mean km	ratio
1	*Rural Residents*	739	53	7.17	228	137	147	318	0.93
2	*Cosmopolitans*	235	111	47.23	29	21	31	198	0.68
3	*Ethnicity Central*	444	238	53.60	62	45	69	121	0.65
4	*Multiculural Mets*	1011	281	27.79	207	136	174	214	0.78
5	*Urbanites*	1481	226	15.26	331	219	252	259	0.87
6	*Suburbanites*	1666	152	9.12	400	244	266	257	0.92
7	*Constrained City*	525	229	43.62	70	55	79	211	0.70
8	*Hard Pressed*	1227	352	28.69	197	143	184	236	0.78

Non-home chargers always charge their car if they arrive at a destination with a charger.

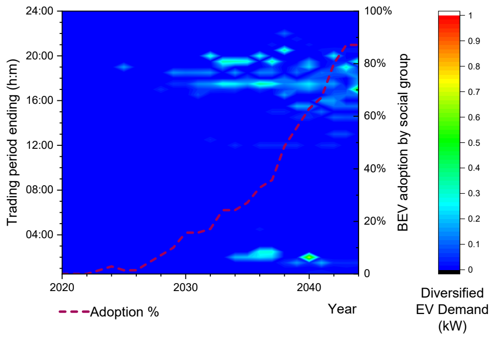
In Figure 8.6 the diversified charging demand and individual adoption are shown for the uncontrolled charging strategy. The *Constrained City* and *Multicultural Mets*, both being city dwellers but with different income profiles, exhibit some similar characteristics, although the more wealthy *Multicultural Mets* are using their cars in the evenings which results in charging demands around 10pm. Both groups cover fewer miles than suburban and rural drivers (see Table 8.1), meaning lower weekly energy requirements, but with both adoption rates and car ownership being higher amongst *Multicultural Mets*, there is a little more impact on the system. A further factor affecting local demands is that both groups have lower access to home charging compared to the mean (see Table 3.7), only about half of charging demand is presented in these charts.

Suburbanites show a much more pronounced impact, though peaks are still only around 0.5kW by end 2044. There is also some early and late charging activity, which may reflect school runs and use of cars for more evening trips. The *Rural Residents* exhibit the most pronounced peak, with occasional 1kW maximums. This is likely to be the result of this group making longer journeys resulting in more overlapping charging events. The challenge for *Rural Residents* is that the peak appears earlier than some other groups and overlaps the normal evening peak in what can be already weak grid systems. There is a further potential issue for *Rural Residents* in that the dispersed nature of properties also tends to mean that there are fewer properties per electricity feeder, resulting in less diversification of demand [19] and greater potential for system overloads.

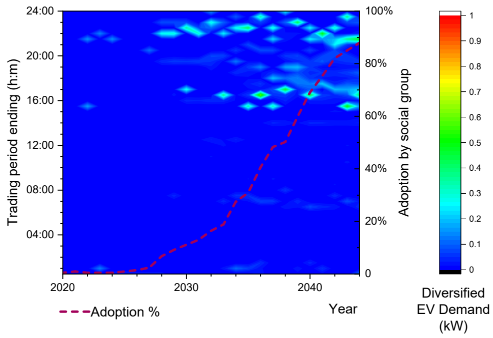
An important consideration here is that these demands comprise only household power flows. The *Hard Pressed* and *Multicultural Mets* are both less likely to have access to home charging than suburban or rural households (54% and 63% vs 84% and 81% - see Table 3.7). Thus true locational demands may also depend on the nature of alternative charging provision; kerbside charging and local hubs may increase demand in the same locales as illustrated here, whereas work-based or destination based charging (e.g. during a supermarket shop) might not. Whether this latter additional charging presents a problem to network operators is, however, a moot point given that any such charging provision would require direct involvement of the Distribution Network Operators (DNOs) anyway. Figure 8.5 illustrates the impact if all car owners are able to charge locally to their homes. Having such home charging provision also impacts slightly on uptake rates as shown in Figure 8.7, which indicates that demands are likely to rise more quickly where access to charging near home is provided. Here, the *Constrained City* and *Multicultural Mets* begin to show some higher demands from the late 2030's (60% penetration). However, in the case of *Constrained City* dwellers the major peak occurs after the afternoon commercial peak and the *Multicultural Mets* peak very late in the evening after even the main residential high demand period. Thus it seems likely that city residents may be relatively easy to accommodate within the constraints of existing network infrastructure to 100% penetration. The difference in presented demands for *Suburbanites* is relatively small due to the high proportion of this group with access to home charging (84%). For *Rural Residents*, whilst a significant proportion (81%) already have home charging, the longer distances travelled and thus greater opportunity for overlapping charging periods, do result in more occasions where local demands are significant and this begins to show up much earlier, from the early 2030's at only 20% adoption.

Figure 8.8a plots the demands from all social groups across a week at the end of 2044. These demands are shown added to the default household profile class 1 (winter) [78]. The profile class is an average demand profile used in the electricity market settlement process for domestic consumers. This chart also shows that *Rural Residents* contribute significantly to the demand and that this demand is overlaid onto to the existing domestic peak.

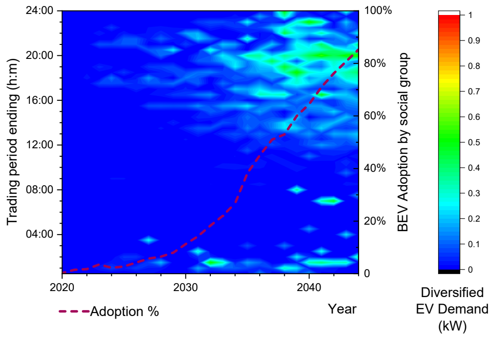
Final distribution feeders can supply very few households (particularly in rural areas) up to several hundred in more densely populated locations [48], but generally cover a relatively small geographic area. As such, the demands seen at the distribution transformer will often be those related to a single (or perhaps two or three in an urban centre) social group. The demand plotted in Figure 8.8a will be more representative of load contributions at higher voltage levels and indicative of the additional generation required. With design ADMDs ranging from



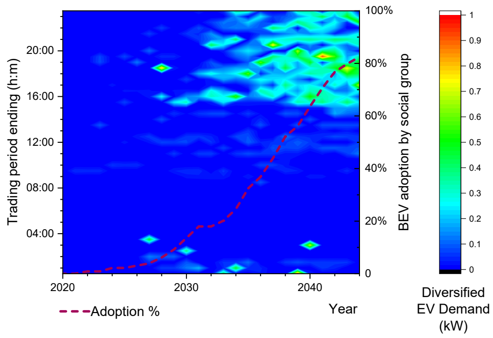
(a) *Constrained City*



(b) *Multicultural Mets*

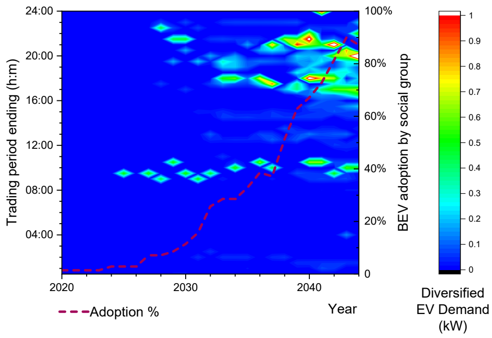


(c) *Suburbanites*

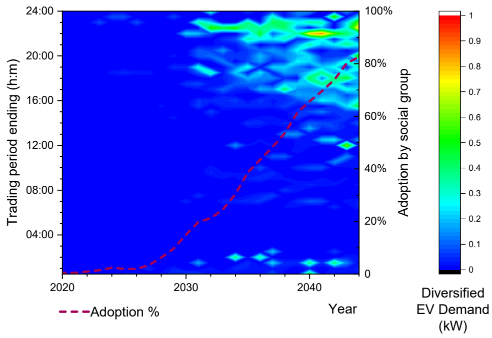


(d) *Rural Residents*

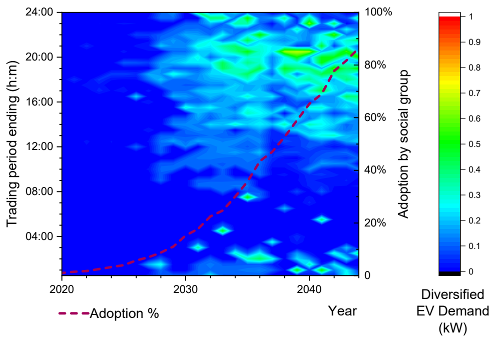
Figure 8.5: Uncontrolled household diversified weekday charging demand profile and BEV adoption over time for selected social groups. (a) *Constrained City*. (b) *Multicultural Mets*. (c) *Suburbanites*. (d) *Rural Residents*.



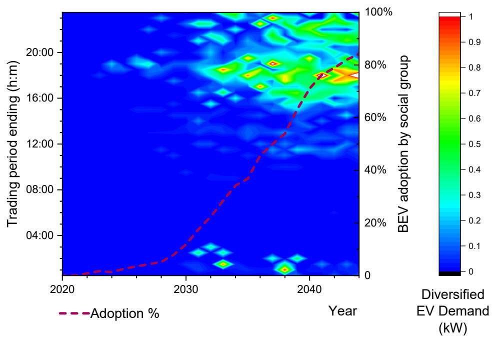
(a) *Constrained City*



(b) *Multicultural Mets*



(c) *Suburbanites*



(d) *Rural Residents*

Figure 8.6: Uncontrolled household diversified weekday charging demand profile and BEV adoption over time for selected social groups where it is assumed all drivers have access to home or street charging. (a) *Constrained City*. (b) *Multicultural Mets*. (c) *Suburbanites*. (d) *Rural Residents*.

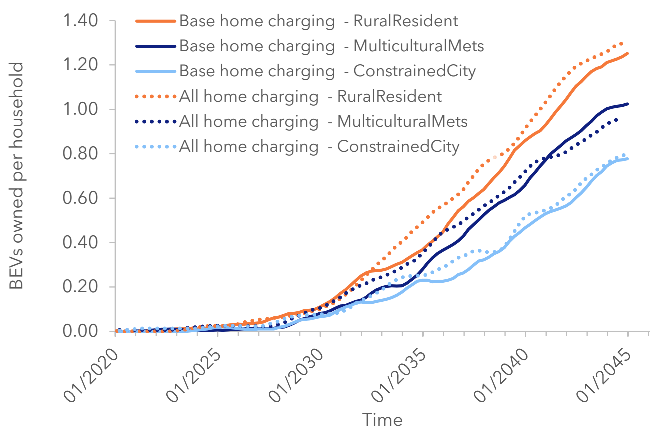


Figure 8.7: Number of BEVs per household showing impact of home charging availability

1.2kW to 2.4kW (depending on house size) where gas heating is used (assumed for profile 1 customers), it can be seen from Figures 8.6 and 8.8a that EVs may present problems relatively quickly in rural locations with uncontrolled charging, although in urban environments, there appears to be less of an issue up to relatively high penetrations of over 80% due to lower ownership levels and fewer miles being driven. However, in the case where all homes are assumed to have access to local charging, Figure 8.8b, there is an interesting anomaly at weekends, where it appears that city dwellers, particularly *Multicultural Mets*, are using their cars more extensively requiring a substantial early evening charge, which leads to high weekend peaks.

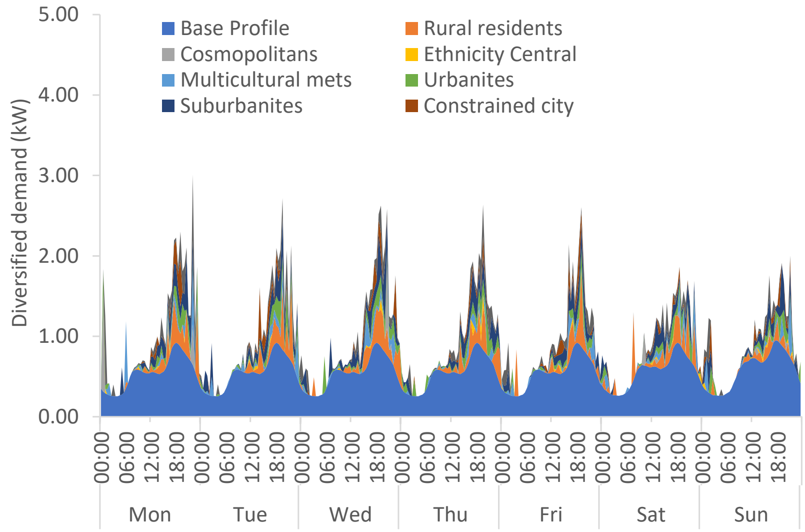
8.2.2 ToU charging

In this scenario, drivers are assumed to plug-in and charge as soon as practical. The model differentiates between those with home chargers and those without as follows:

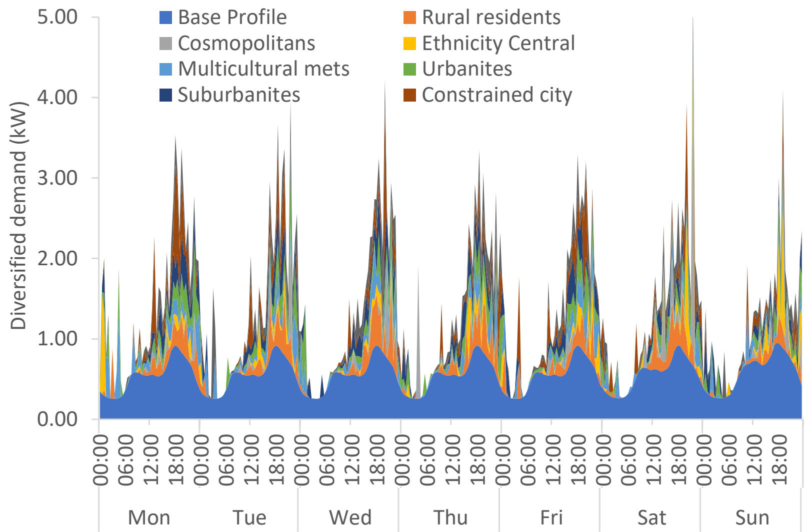
Home chargers only charge away from home if they are unable to complete the next journey, plus their individual comfort margin, on their current battery charge. If they arrive home and are similarly unable to complete their next journey without charging they will charge immediately, if they do have sufficient charge, then their charging will be delayed until the start of the ToU period.

Non-home chargers always charge their car if they arrive at a destination with a charger, but this will not be visible in the base residential charging profiles.

Figure 8.9 illustrates the diversified charging demands for ToU charging with a single ToU start time of midnight. Whilst this is currently an option offered by many suppliers (with only marginally variable start times of between midnight and 1.00am), it clear that this not a sustainable solution for networks. Although city centre locations may be able to cope with such demands because of the lower ownership and that commercial demands would be low at this time, even these locations show signs of potential network stress. Suburban and rural networks would be under stress at penetrations of 30%. The challenge presented by continuing this simple strategy is clearly indicated in Figure 8.10, with peaks regularly reaching five times the base profile assumption. Research by Delmonte et al. [53] suggests that ToU type tariffs are preferred over more complex smart-charging arrangements since the driver maintains control of vehicle charging and achieving the required range by the time of departure, but it is clear here that a simple ToU

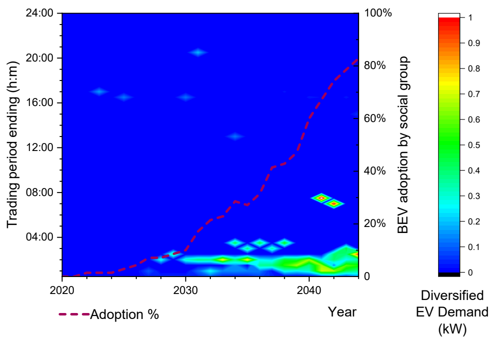


(a) Uncontrolled - base home charging

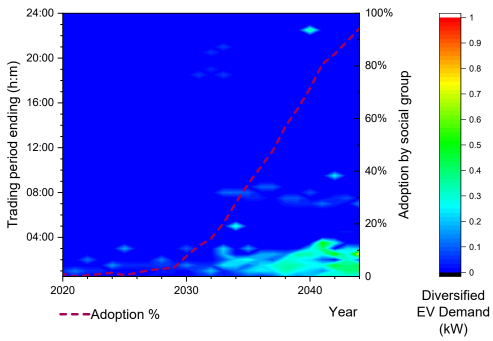


(b) Uncontrolled - all home locale charging

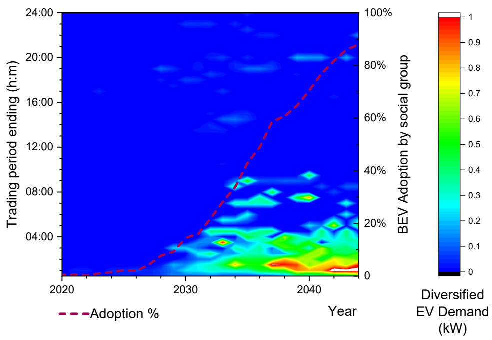
Figure 8.8: Uncontrolled diversified charging demand for all groups across week at end of 2044, superimposed over the Profile Class 1 (winter). (a) Assuming only home chargers contribute to local demand. (b) Assuming all car owners contribute to local demand.



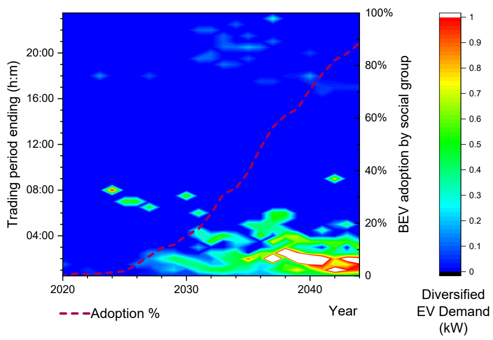
(a) *Constrained City*



(b) *Multicultural Mets*



(c) *Suburbanites*



(d) *Rural Residents*

Figure 8.9: ToU household diversified weekday charging demand profile and BEV adoption over time for selected social groups. (a) *Constrained City*. (b) *Multicultural Mets*. (c) *Suburbanites*. (d) *Rural Residents*.

strategy is unworkable. Adding additional street/local charger demands would clearly confound this situation and thus are not presented here.

8.2.3 Controlled charging

It is apparent from the analysis above that both uncontrolled and simple ToU charging strategies are likely to present local network and potentially national generation, problems. This has been identified in the literature as a potential issue [105, 185] and various solutions proposed [105, 140, 186], but these invariable require sophisticated communications and data aggregation. One unacknowledged challenge to these solutions is that home EV chargers employing the current 'type 2' (IEC62196) and UK 'smart type 2' [232] specifications, do not require the charger to obtain the current vehicle battery state of charge. This means that any smart system is unable to accurately forecast the time before which charging must commence to achieve adequate range for the next journey. Indeed, there is, in effect,

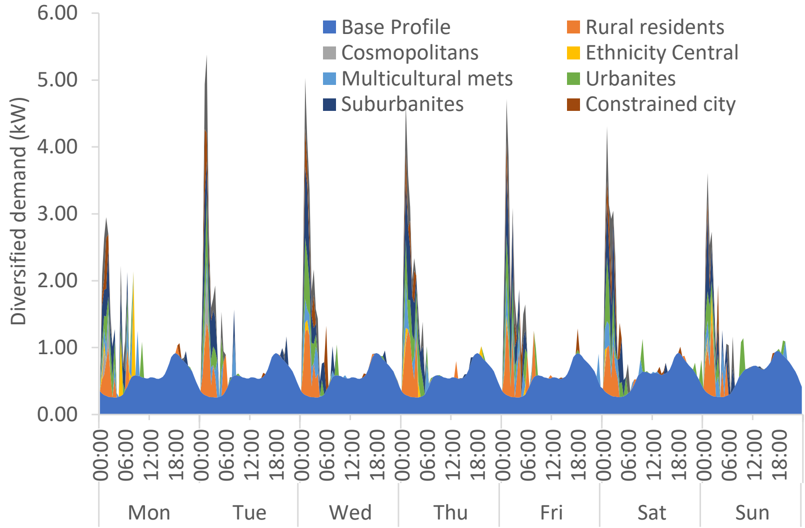
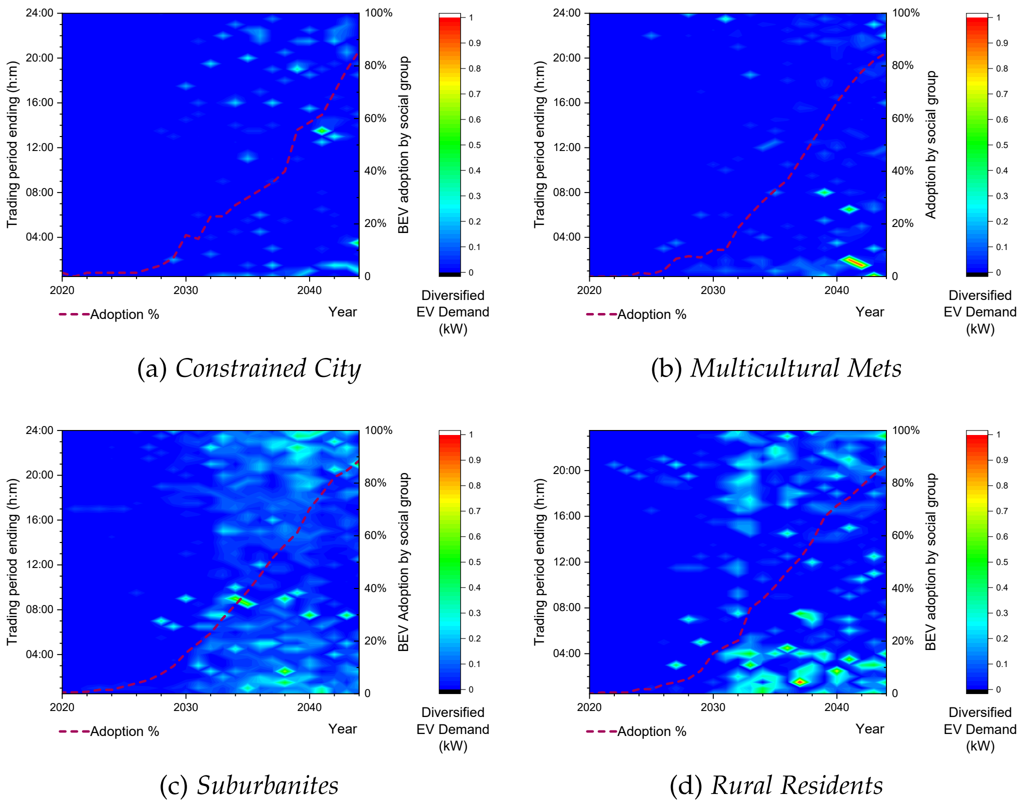


Figure 8.10: ToU diversified charging demand for all groups across week at end of 2044, superimposed over the Profile Class 1 (winter).

no communication between the car and charger beyond safety checks and maximum charge rate available from the charger. These features are likely to further reinforce distrust in the ability of remotely controlled smart charging solutions to meet driver requirements. In this section, a charging algorithm that does not require any external communications and could be implemented entirely within the vehicle is tested to assess its impact on home-based charging profiles. The smart charging algorithm is described in Section 3.11.3. An important aspect of this algorithm is that cars will charge immediately on plugging in if they have an estimated range (based on average driving efficiency) of 100km or less; this threshold was chosen to correspond to the typical point at which an ICE car low-fuel warning comes on, but these thresholds may be lower for established BEV drivers, which would result in less peak time charging.

Figure 8.11 shows the effect of this algorithm on demands for four groups explored and indicates that it is effective at reducing peak demands for all groups. Even when all drivers are given access to local charging, Figure 8.12, the demands are relatively well managed, although there are occasional concerning peaks. These indicate that such an algorithm may not be successful at 100% EV use, although adoption of a lower minimum range requirement (which in practice might be set by individual preference with some cost penalty to higher ranges)



(a) *Constrained City*

(b) *Multicultural Mets*

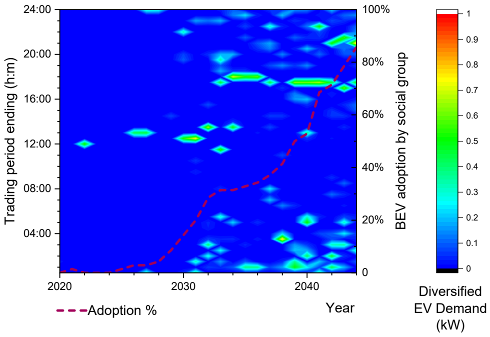
(c) *Suburbanites*

(d) *Rural Residents*

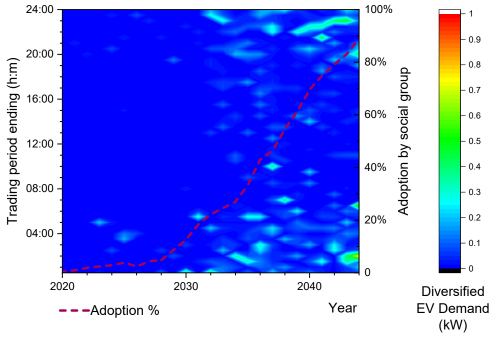
Figure 8.11: Controlled household diversified weekday charging demand profile and EV adoption over time for selected social groups. (a) *Hard Pressed*. (b) *Multicultural Mets*. (c) *Suburbanites*. (d) *Rural Residents*.

might resolve this.

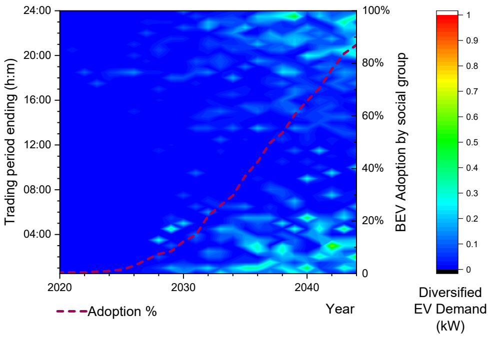
Looking across the 2044 full week profile, Figure 8.13a, the effects of immediate charging can be seen to have a more substantial impact on overall demand at, and shortly after, peak residential load. This is exacerbated by the provision of local charging for all; Figure 8.13b. However, these are driven by unplanned trips rather than regular events, evidenced here by the fact that they originate from different socio-economic groups on each day, but also evident in the underlying data. It is possible that drivers might adopt different strategies before, during and following such unplanned trips, so the accuracy of these spikes is subject to some doubt.



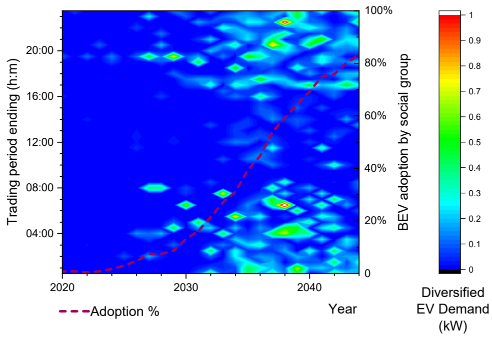
(a) *Constrained City*



(b) *Multicultural Mets*

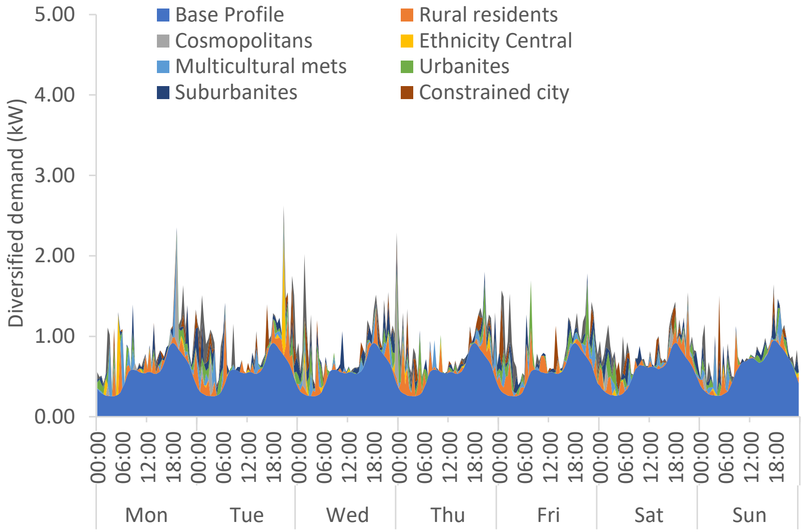


(c) *Suburbanites*

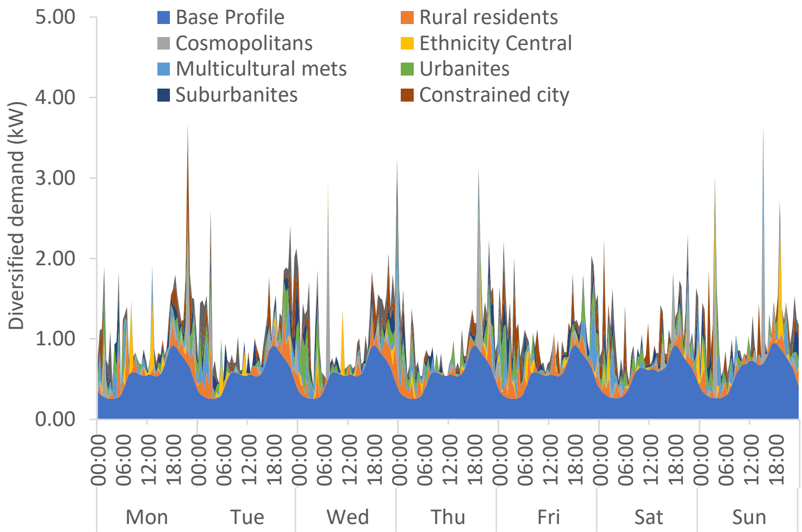


(d) *Rural Residents*

Figure 8.12: Controlled household diversified weekday charging demand profile and EV adoption over time for selected social groups assuming all have access to charging close to home. (a) *Hard Pressed*. (b) *Multicultural Mets*. (c) *Suburbanites*. (d) *Rural Residents*.



(a) Controlled - base home charging



(b) Controlled - all home locale charging

Figure 8.13: Controlled diversified charging demand for all groups across week at end of 2044, superimposed over the Profile Class 1 (winter). (a) Assuming only home chargers contribute to local demand. (b) Assuming all car owners contribute to local demand.

8.3 What storage capacity may be available to grid operators?

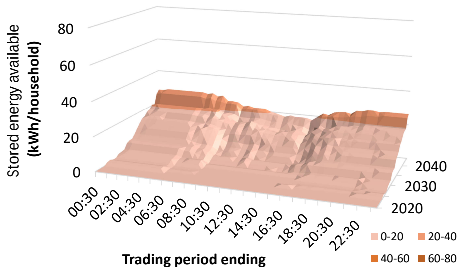
What capacity of energy storage may be available to grid operators?

In this section the energy stored per household through a sample Wednesday each year from 2020 to 2045 is presented for the four geographically discrete social groups. The figures illustrate the capacity remaining in the batteries connected to fast chargers (7.2kW AC nominal), but not rapid chargers, since these will always be charging only, and assumes that they are charged under the 'uncontrolled' scenario, thus connected available energy ramps back towards connected EV battery capacity by around midnight.

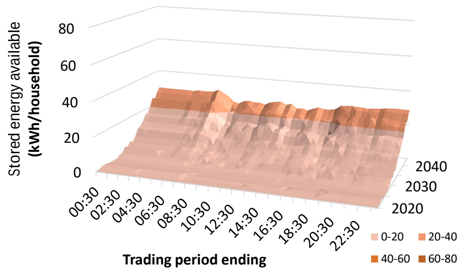
In Figure 8.14, the base assumption for access to home charging is presented. The city centre groups (a and b) show a much less dramatic reduction in connected energy since these groups are less likely to commute to work; cars are connected at home chargers for most of the day. However, lower car ownership and reduced access to home chargers also means that the energy stored per household is substantially lower than for *Suburbanites* and *Rural Residents*. These later groups display a pronounced reduction in connected energy between 6.30am and 8.30am. The *Suburbanites* are also returning home more gradually during the day. Given that the average daily electricity consumption employed in the simulation is ca. 10kWh for non-BEV owners and 15kWh for BEV-owners, the charts illustrate that even in the *Constrained City* area, there is sufficient energy stored for two to three days of mean household use.

The high availability of connected energy in suburban and rural locations is useful in that these are also the where demand issues are most likely to arise. The use of V2G and Vehicle-to-Home (V2H) technology in these locations could thus avoid additional network investment. It is also notable that there is significant capacity connected in the middle of the day, about 30kWh per household, which suggests that there is opportunity to absorb local solar output. This could both enable greater penetration of solar without network upgrades and provide 'generation shifting' capability to move this generation into peak demand hours or to reduce peaks from charging other BEVs. With 27.8million households in the UK [170], 30kWh per household gives a theoretical capacity 834GWh. This is ca. 87% of UK daily electricity consumption, and some 100 times the storage capacity of the UK's largest pumped hydro scheme at Dinorwig in North Wales.

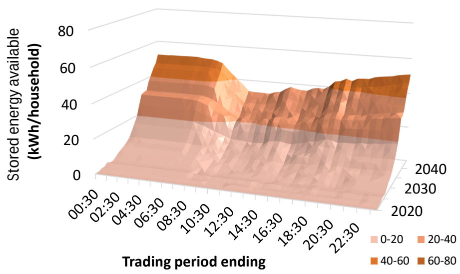
Figure 8.15 considers the case where all cars have access to a charging point local to their home. The city groups now also exhibit a higher drop-off during the middle of the day. This indicates that those city dwellers who commute are



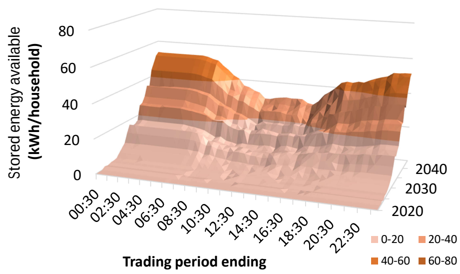
(a) *Constrained City*



(b) *Multicultural Mets*



(c) *Suburbanites*



(d) *Rural Residents*

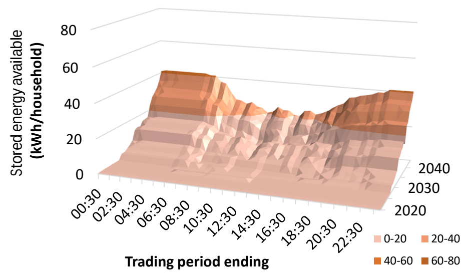
Figure 8.14: Energy stored in connected batteries, base home charging assumption and owners adopt 'uncontrolled' charging. (a) *Constrained City*. (b) *Multicultural Mets*. (c) *Suburbanites*. (d) *Rural Residents*.

more likely to be BEV adopters, reflecting the savings available even to non-home chargers. The connected energy stored for *Multicultural Mets* increases more dramatically since this higher income group has both a higher car-owning percentage and greater adoption.

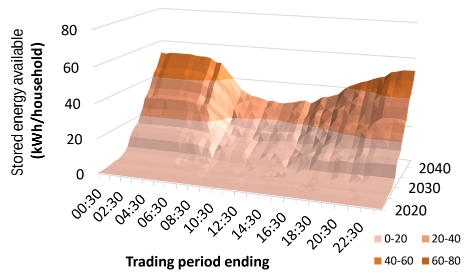
Figure 8.16 considers a perhaps more realistic case, where those without home chargers have a '2/7th' chance of plugging in (i.e. essentially an average of two charges per week where these are of several hours duration) and all drivers have a 50% chance of being able to connect to a charger at work, leisure and shopping destinations. It is clear from comparison with the previous cases that this significantly flattens the profile of available stored energy in the middle of the day.

8.4 Exploring the opportunities from V2G

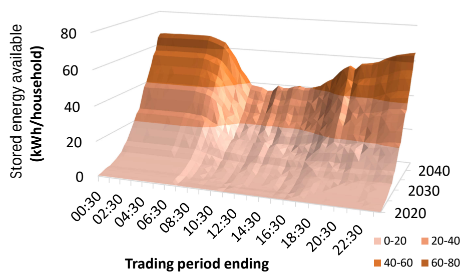
How can BEV battery capacity be applied in a V2G application?



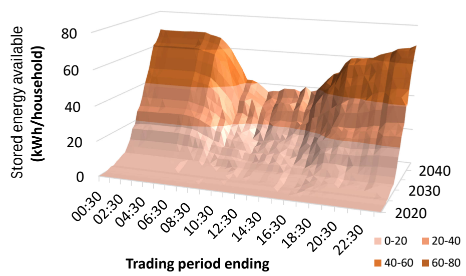
(a) *Constrained City*



(b) *Multicultural Mets*

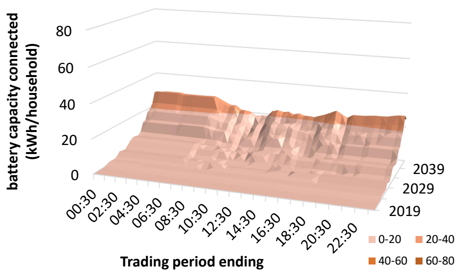


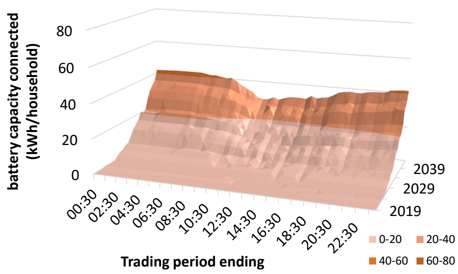
(c) *Suburbanites*



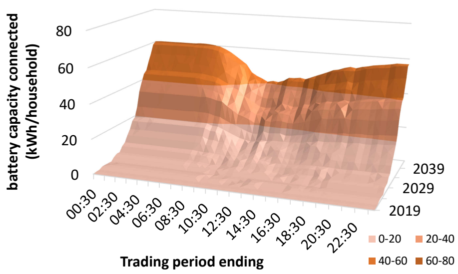
(d) *Rural Residents*

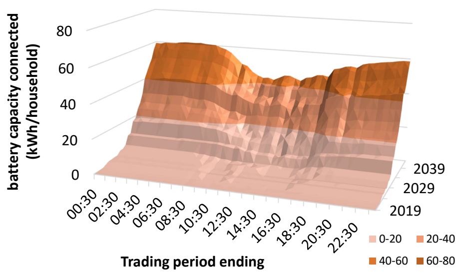
Figure 8.15: Energy stored in connected batteries assuming all houses have access to a connection and owners adopt 'uncontrolled' charging. (a) *Constrained City*. (b) *Multicultural Mets*. (c) *Suburbanites*. (d) *Rural Residents*.





(a) *Constrained City* (b) *Multicultural Mets*





(c) *Suburbanites* (d) *Rural Residents*

Figure 8.16: Energy stored in connected batteries assuming householders without home chargers have a 2/7th probability of connecting to a street charger at home, all drivers have 50% access to destination charging and owners adopt 'uncontrolled' charging. (a) *Constrained City*. (b) *Multicultural Mets*. (c) *Suburbanites*. (d) *Rural Residents*.

In Section 8.2 the challenges posed by additional EV demands were explored and in Section 8.3 the simulated amount of energy stored by EVs in various locations/social groups was established. Clearly this storage capacity could play a role in helping to reduce the impact of peak demands and help to balance intermittent renewable energy production. There are numerous possible ways in which V2G systems might operate. For example, they may operate as V2H where a home owner with an electric car effectively supplies their own household demand at times of high prices. These currently correspond to high demand periods, but in future are likely to align to low renewable generation periods since demands at these times will need to be met from stored energy which will be inherently more expensive. For local utilities, V2G may operate to help manage power flows within the distribution system, enabling the connection of more embedded generation and reducing the need for system reinforcement to provide for greater demands from EVs themselves, but also from the electrification of heat. Alternatively, V2G might be more focused at the transmission, or country, level, attempting to absorb excess wind and solar and supply it back to the grid when needed. Whilst these options have certain common features, they may also conflict; the need to absorb large volumes of excess renewable generation from remote locations (e.g. offshore wind) may not be compatible with maintaining power flows within design limits at distribution level. To explore these issues, the simulation was run using the V2G algorithm introduced in Section 3.11.4. Since the focus here is on impacts within our social groups, the system demand is modelled as the base household profile plus the demand (or less generation) from the electric vehicle fleet. The installed capacity of generation is increased each month such that the mean annual energy output is 15% above the expected annual demand from the base household profile and all current BEV owners.

8.4.1 Country-level impacts of V2G

In this section simulation results that explore the impact of V2G at the overall system level are presented, although figures are representative of the 1000 homes (1524 car owners) used in the simulation. Figure 8.17 presents an EWMA of the half hourly unserved energy (see Equation 3.14, but using an alpha of 0.001389, corresponding to 30 days of half hourly data). Unserved energy here is defined as the energy in the half hour period that could not be supplied from wind, solar or EV discharge in that period. An EWMA is used to make the data more readable over the 10 years presented, but it should be born in mind that the duration of storage available in EVs means that many short term spikes are hidden. The dotted lines show a linear fit to the data and indicate that increasing EV penetration,

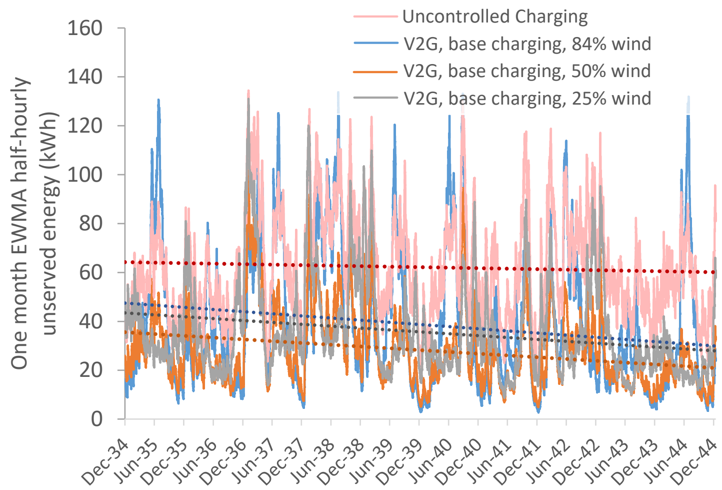


Figure 8.17: Comparison of uncontrolled charging with three wind to solar ratios on V2G effectiveness at balancing the system, measured as an EWMA (over one month of half hourly samples) of unserved energy, i.e. shortfall from a combination of wind, solar and EV discharging. The dotted lines are a linear fit to the data showing the general trend for a reduction in unserved energy as EV adoption grows.

in parallel with an increase in generation proportional to the additional EV energy use, reduces the unserved energy by ca. 40%. The 84% wind (16% solar) ratio scenario is drawn from the work of Caredenas et al. [38] and is based on an optimum mix assuming UK total system demand profile over the nine years from 2011 to 2019. This includes industrial loads and therefore there is a higher base demand for electricity throughout the year than in the simulation here. This scenario indicates significant unserved energy during summer months, reflecting periods of low wind generation, and so two other scenarios are presented; a 50% wind case and 25% wind case. In the 50% wind case, a substantial reduction in unserved energy is seen, with much lower peaks in the summer months. However, reducing the proportion of wind still further leads to an increase in unserved energy in winter months. Thus the most appropriate mix of wind and solar within a future UK grid is likely to be heavily dependent on how demands evolve, i.e. the extent of the electrification of transport and heating. The addition of EVs with their own built-in medium duration (i.e. up to a few days) storage and the availability and uptake of V2G will be a significant factor.

Figure 8.18, with expanded vertical scale for clarity, adds scenarios for access to V2G. The ’all home’ scenario assumes that all homeowners can access a V2G

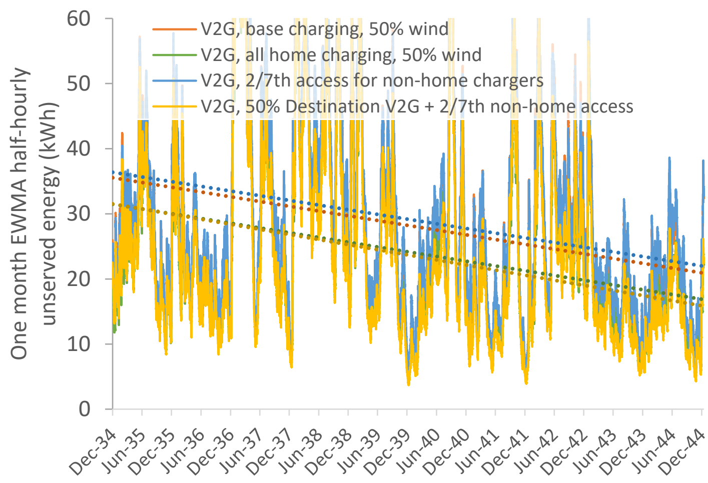


Figure 8.18: Comparison of 50% wind scenario with base home charging and where all homes have access to V2G capability, measured as a monthly EWMA of unserved energy.

enabled charger whenever they are at home, showing a substantial decrease in unserved energy. However, it is highly unlikely that sufficient street charging provision can be made available to provide connections for all car owners every night. The '2/7th access' scenario assumes that those without a home charger have access to plug in on 2 out of 7 occasions that they arrive home. There is no constraint here on the actual number of chargers, but this should be broadly equivalent to car owners having access to charge for two days out of every week, enough to satisfy the needs of all but the highest mileage drivers with forecast battery sizes. This reveals an interesting outcome, whereby unserved energy is actually higher than in the case where no V2G is assumed for those without home chargers. This occurs because the algorithm only looks forward to the end of the following day when determining whether a V2G connected BEV should charge or discharge. Thus cars may discharge and subsequently be unable to re-charge during a low demand/high generation period, meaning that they then recharge either at rapid chargers or destination chargers in an 'uncontrolled' manner, that is, disregarding current generation balance. Whilst this is, to some extent, an artefact of the algorithm, it is also transferable to the real world, in that to gain the most benefit, the same cars needed to be connected most of the time to avoid individual cars running short of charge. One way to overcome this would be to ensure that drivers have access to V2G enabled connections other than at home. This is illustrated in

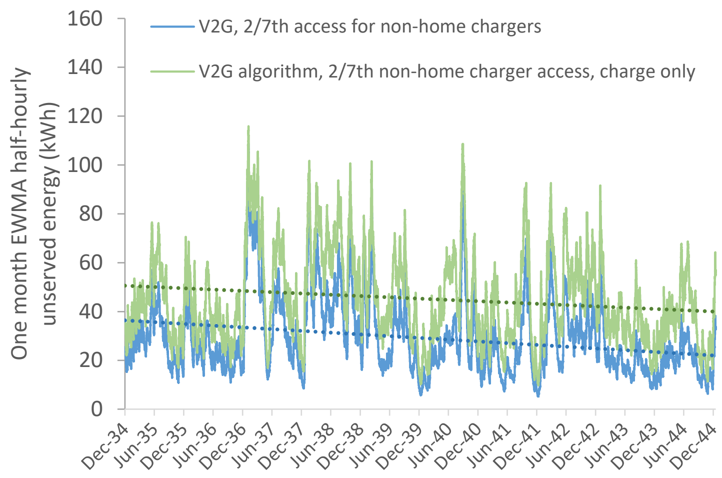


Figure 8.19: Comparison full V2G algorithm with 'charge-only' variant of same strategy.

the fourth scenario, '50% destination V2G + 2/7th non-home access'. Here, drivers are given a 50% probability of being able to connect to a V2G enabled charger at work, shopping and social (entertainment) destinations. Adding this V2G provision reverses the the effects of reduced home access and results in a marginal improvement on unserved energy at high levels of BEV adoption compared to giving all drivers full access to home-only V2G.

Prior to BEVs reaching the market, the monthly average unserved energy is approximately 65kWh per half hour period for the 1000 home sample. Over a full year, and across 27.8million homes [170], this amounts to 31.66TWh of unserved energy, which can be reduced to one third that with comprehensive adoption of V2G. One question arising here is, to what extent is V2G rather than simply smart charging delivering this benefit? Figure 8.19 shows that if the algorithm is modified such that cars do not enter the discharge mode, then there is significant benefit over the uncontrolled charging case (Figure 8.17), but not to the extent of the full V2G scenario. However, this case does not require all chargers to be V2G enabled and results in a much higher distribution of mean SoC for the fleet; always remaining above 60% (not illustrated). This might therefore represent a more consumer-friendly option which enables significant benefits to be delivered, including low cost charging for non-home chargers.

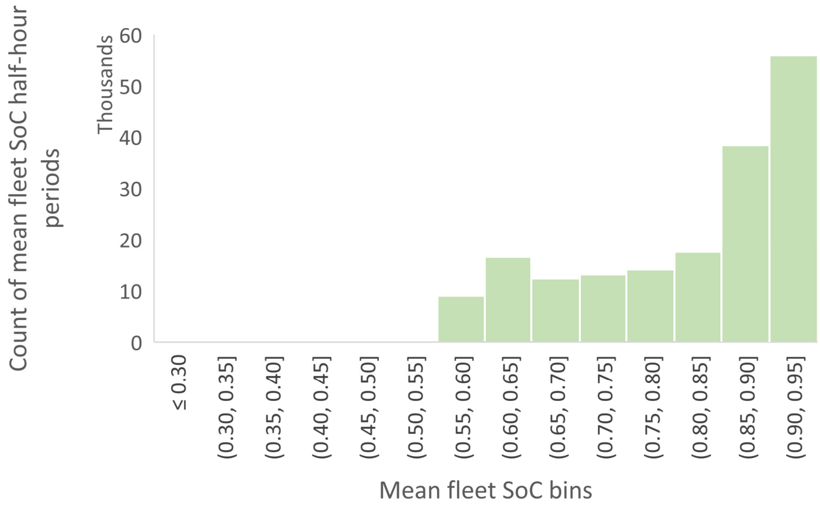
8.4.2 Driver behaviour and minimum SoC limitations

A key feature in the effectiveness of V2G is the willingness of consumers to allow their vehicle to be discharged. Whilst the behavioural modelling here is limited, driver agents have a wide spectrum of minimum range requirements which, added to driving requirement up to the end of the following day, constrain the minimum SoC for each car. Figure 8.20 compares the distribution of mean SoC of the fleet over 10 years of variable generation and V2G response with 84% and 50% wind. Whilst not shown graphically here, in the uncontrolled charging scenario, the mean SoC of the fleet is above 80% at all times. In essence, the minimum mean SoC is set by driver requirements in both cases, although some drivers will, individually, accept much lower SoCs than the minimum shown here, it can be seen that the EVs are maintained at a relatively high SoC for most of the time, which one might expect to be reassuring for drivers. Conversely, occasional drops to low SoC could be more distressing due to their relative rarity. The higher solar case (b), provides the driver with more time at high SoC and may be more reassuring than the wind case.

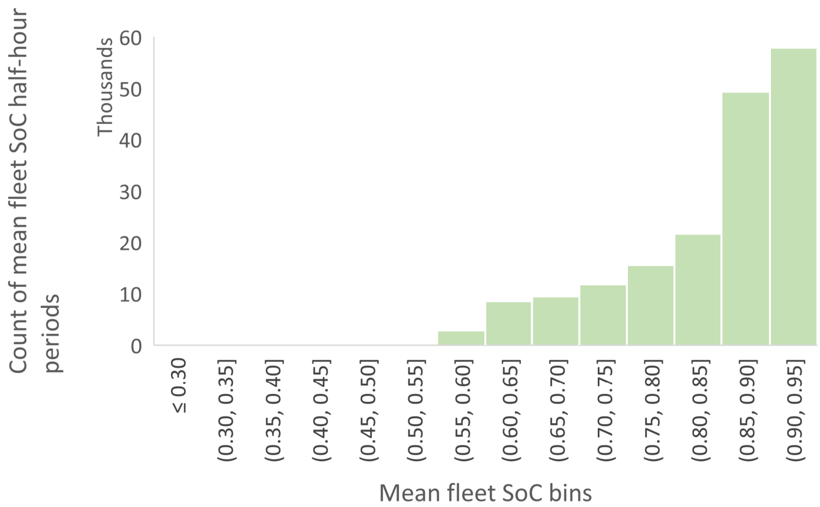
8.4.3 Local and short time-frame V2G impacts

Section 8.4.1 explored how EVs might help at system level, balancing wind and solar generation. In this section, the impacts at more granular timescale and spatial conditions are reviewed for a sample week.

84% Wind scenario Figure 8.21, for the 84% wind case, illustrates the demand from the full 1000 household data set with charging demand added; areas where the charging demand breaks into the household profile (such as Tuesday daytime) indicate that cars are exporting since household demand is greater than generation. Over the first three days of low generation, the mean SoC of the fleet is generally decreasing, although wind generation remains sufficiently high at night to enable some recharging. On Monday and Tuesday evenings cars require charging to meet the following day's driving requirement, and this gets added to the system peak. This is, to some degree, an artefact of the algorithm, which instructs cars to charge immediately if there is insufficient charge for the next day. Thus an improved algorithm could delay charging, where sufficient range is available for any evening trips, until the early hours of the following morning to avoid adding to the peak. On the Wednesday, when wind generation picks up, charging demands also ramp up, following the excess generation and bring the fleet back to close to 100% SoC. However, in this high wind case, there are insufficient vehicles



(a) SoC histogram 84% wind over 10 years



(b) SoC histogram 50% wind over 10 years

Figure 8.20: Histograms showing distribution of mean SoC of electric vehicles over 10 years of variable generation

connected during the day to absorb all generation. Enabling more V2G at day-time parking locations (work, shopping etc.) would help to absorb this spare wind.

Figure 8.22 breaks down the charging demand into the four groups previously analysed. These will not sum to total charging demand since not all groups are shown and nor are non-home or rapid charges. The purpose of presenting this data is to explore how local network demands may be impacted and how the cars of different social groups respond. On the per-household basis illustrated, a different weekend pattern is observable for city-centre dwellers, where cars are used more and there is more charging activity. During the weekday charging activity (Monday evening onward), the picture is largely reversed. During the evening peaks the mean household demand fairly closely tracks the base household profile; most cars are in the 'do nothing' state, but some maybe discharging to balance those that need charge. The rural car picture becomes interesting on weekdays and appears to be a result of the higher V2G availability of this group in the middle of the day. That is, those cars not used for commuting by the city-centre dwellers are less likely to be connected and available for V2G due to the lack of home charging, whereas rural cars that are not in use are more frequently connected for V2G. There is a similar, though less clear, pattern for suburban cars, more of which are used for commuting and for morning trips, but can be seen to be available and discharging on, for example Monday afternoon, as generation falls below demand. By this time, rural vehicles are reaching the minimum range requirement and switch to the 'do-nothing' state. When generation picks up, there is a rapid increase in charging demand in the rural group with a 1.7kW ADMD, substantially more than other groups and potentially exacerbated by the discharging that occurred during the previous day as more car charging events overlap. The much lower car ownership and V2G access amongst the *Constrained City* group means that whilst their per household net demand does not often fall below zero, individual cars may actually be contributing substantially to demand balancing.

50% Wind scenario Figure 8.23 shows the situation with 50% wind generation. In the first three days, despite being a December week, there is sufficient solar generation to enable cars to charge in the middle of the day. The mean SoC, however, continues to fall, with limited spare generation for overnight re-charging as in the 84% wind case. As wind generation ramps up, charging follows, but in this case, there are sufficient vehicles connected at all times to absorb the total generation, though this is because the peak generation is lower rather than there being more capacity to absorb it.

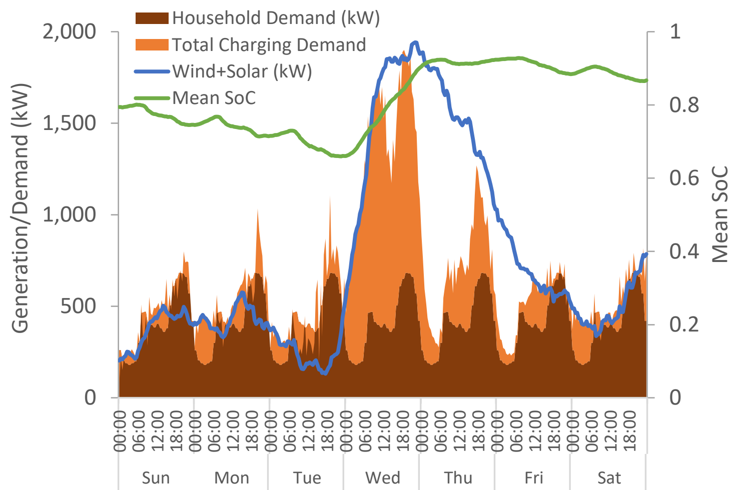


Figure 8.21: Sample week of V2G operation with 84% wind illustrating how total charging demand is matched to generation and car discharge to meet demand.

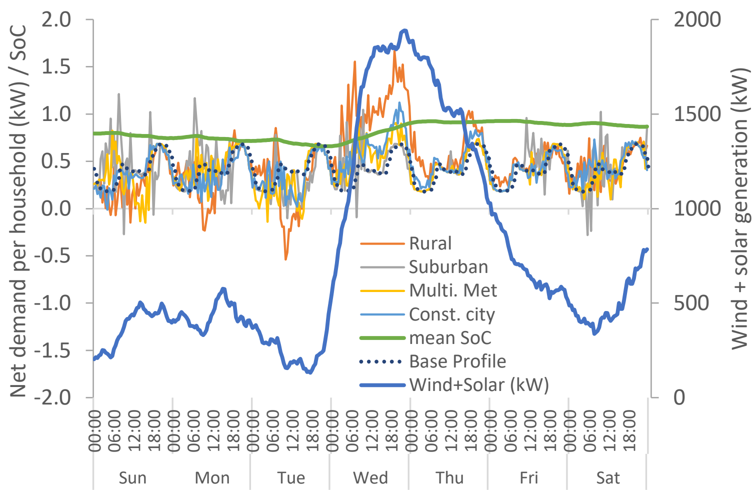


Figure 8.22: Sample week of V2G operation with 84% wind over highly variable wind speed week (end Dec 2044) showing how each of our four sample social groups respond and the impact on mean SoC of the BEVs.

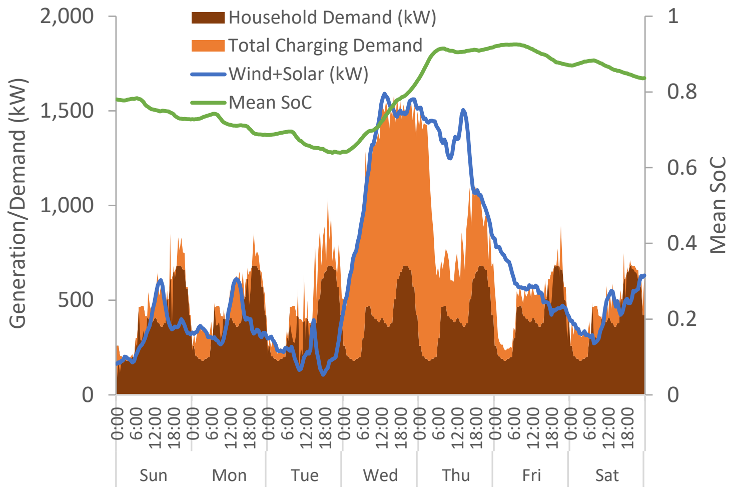


Figure 8.23: Sample week of V2G operation with 50% wind illustrating how total charging demand is matched to generation and car discharge to meet demand.

In the social group breakdown, Figure 8.24, a similar pattern to the 84% wind case is visible, but with slightly greater discharge of vehicles during low generation periods since they have been able to charge more with daytime solar generation. The rural ADMD is reduced from 1.7kW to 1.4kW, with fewer cars charging concurrently due to lower evening generation.

50% Wind + enhanced V2G scenario Figure 8.25 adds greater access to local-to-home V2G for those without home chargers (2/7th access) and 50% V2G at work, shopping and social locations. This illustrates some significant benefits to this level of enhanced V2G access. Firstly, being charged more during the day and therefore with greater discharge capability, or simply less need for immediate charging on return to home, the evening peak is rarely impacted by additional charging demands. Secondly, the cars are better able to manage down the peaks in domestic demand during periods of low generation. Whilst they are not reducing the actual peak here, an algorithm better focused on managing peak demand, or potentially a simple V2H strategy rather than V2G strategy, might help minimise peak demand during episodes of low generation.

Figure 8.26 shows the distribution of mean battery SoC over 10 years of half hour periods for this case. Compared to Figure 8.20, there are lower SoC periods, due to day-time discharging of cars that would not otherwise be connected, during low generation. However, some 42% of half hourly periods have a mean fleet SoC

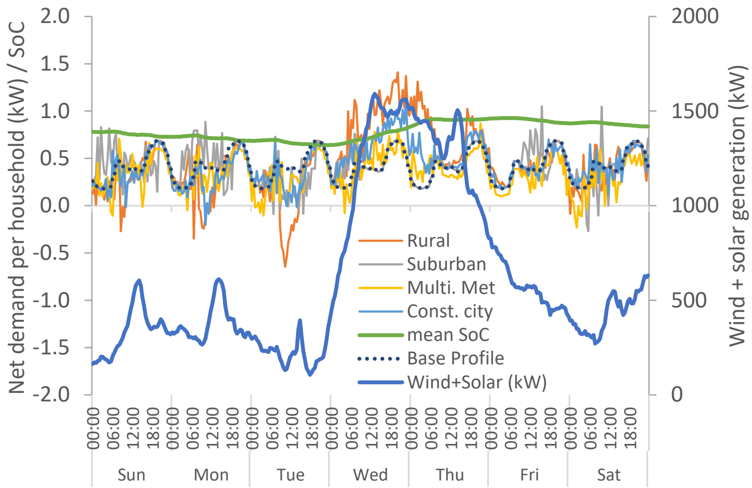


Figure 8.24: Sample week of V2G operation with 50% wind over highly variable wind speed week (end Dec 2044) showing how each of our four sample social groups respond and the impact on mean SoC of the BEVs.

of 85-90%, indicating that vehicles will often be charging during the additional time they are connected. This is due to the large amount of solar in this scenario, which ensures that there is frequently excess generation in the middle of the day when many cars could be connected in V2G mode at work.

8.4.4 V2G conclusions

The heuristic algorithm used here, which prioritises country-scale renewables balancing over distribution network demand control, shows that V2G can make a contribution when individual driver preferences on range are taken into account. What is not considered here are the important edge cases, where consumers may opt to unplug their car when they have seen several days of reducing SoC. This might be overcome by adopting a V2H plus charge on high renewables strategy such that consumers see a more direct benefit themselves. It is also important to note that adoption of V2G is not being modelled, the simulation is assuming that all car owners given access to V2G will adopt it. Despite the high-level balancing algorithm employed here, the ADMD on rural networks in the sample week, with 50% wind and without additional V2G access, is similar in magnitude to that obtained from the basic controlled charging algorithm (1.36kW compared to 1.40KW). This indicates that country-scale renewables balancing is feasible using BEVs connected within the distribution system. However, the balance of wind

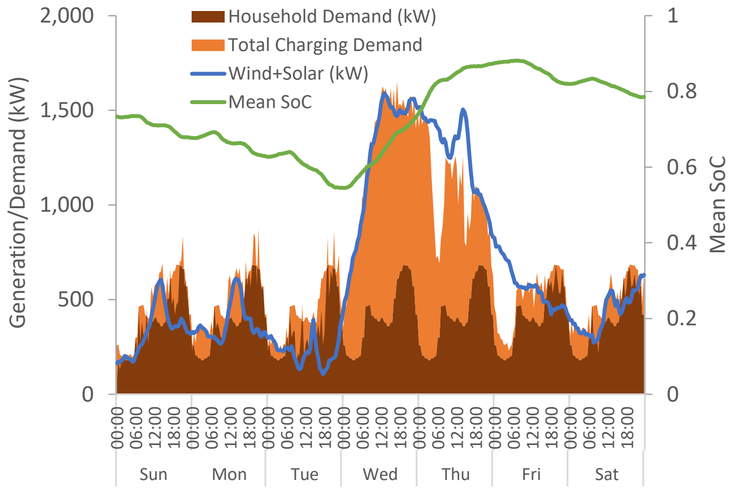


Figure 8.25: Sample week of V2G operation with 50% wind, 2/7th access to V2G for non-home chargers at home and 50% access at work, social and shopping locations, illustrating how total charging demand is matched to generation and car discharge to meet demand where possible.

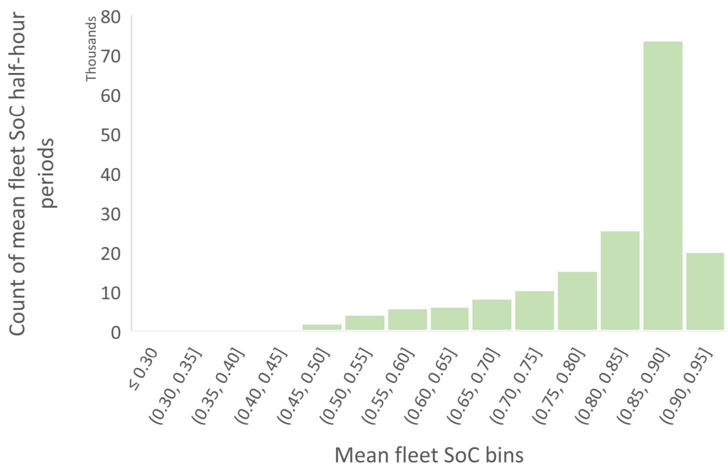


Figure 8.26: Histogram showing distribution of mean SoC with 50% wind, 2/7th access to V2G for non-home chargers at home and 50% access at work, social and shopping locations.

to solar may also be important. Crucially, the bulk of the UK's wind generation will be remote from consumers, much of it offshore, thus power must flow from transmission through all stages of distribution to reach final consumers, increasing the probability of meeting a constraint. Solar, at the current time, is exclusively embedded in distribution networks and significant volumes of roof top solar can sit within the final feeder where EVs may be charging. This suggests that a higher proportion of distributed solar may be beneficial for the deployment of EVs in reducing network reinforcement and losses. To maximise the benefit of embedded solar PV also requires vehicles to have access to daytime charging. It is also important to consider that simple home 'solar-to-EV' control is unlikely to be effective since the standard for type-2 home EV charging limits the minimum power to 1.3kW, meaning that there are frequent occasions when individual domestic solar systems will not be generating sufficient excess power for home EV charging. What is needed is a 'community-scale' viewpoint, where solar from several domestic systems is combined to enable cars to sequentially charge, or where larger scale (100kWs to MWs) of commercial distributed solar is installed.

Whilst the merits of V2G have been discussed extensively in the academic literature, and explored from a new angle here, as of 2020, there is still only one model of car, the Nissan Leaf, that supports V2G. This is implemented through the car's Chademo DC charging port and requires an expensive off-board inverter (£5,500 per unit in the Electric Nation programme [89]). It now appears that BEV manufacturers are starting to build in the capability for bi-directional power flow through the standard Type-2 connector used for domestic charging, with announcements from Hyundai/Kia and VW group. The widespread implementation of on board conversion, which is inherently less costly as it is able to use parts of the vehicle's on-board charger, and the application of the necessary standards for connection to the home, are essential to enable cost-effective uptake of V2G.

To deliver maximum benefit, a significant number of public chargers are also required. Assuming that around 32% of drivers cannot access home charging, then around 10 million cars require public charging. For street charging, it is reasonable to assume that, on a typical day, a charger is used for one car during the day and one car overnight, requiring 715,000 chargers to enable two charging opportunities per week.

The working population of the UK is roughly equal to the number of cars in the country (about 32 million - [231]), of which 18% are shift workers [112] and could share chargers, whilst some 68% commute by car or van [227]. It is also likely that this includes those who travel for work; no data could be found for this, but given that only about 8% of vehicles are company cars (estimated from

[199]) and not all are used everyday for work purposes, it might be reasonable to assume 65% of cars are parked at work. This suggests that 8.5 million work place chargers (which includes public car parks and non-residential city streets) might be needed to meet the connection levels modelled. Persuading drivers to plug in when they already have sufficient range will also be a major challenge, but might be overcome by the use of automatically connecting wireless charging bays, a technology in its infancy today.

8.5 Social equity implications

What are the social equity implications of these demand increases and access to charging?

It is clear from the demand profiles illustrated in Section 8.2 that different social groups present different challenges to the networks. *Rural Residents*, often living in areas where load diversification is reduced due to a smaller number of customers per feeder, and where demand increases may quickly result in supply voltages falling outside of specification due to long feeder lengths, present the greatest demands on the network. The second highest impact group are the *Suburbanites*, where there is perhaps less of a network challenge. Both these groups also contain some of the highest income households, with ca. 50% of each falling into the highest two income quintiles (see Figure 7.10). The *Constrained City* group impose the lowest system impacts, due to a mix of lower car-ownership, reduced mileage and reduced access to home-based charging.

In this section, the implications of the demand profiles presented in Section 8.2 and access to charging and V2G opportunities on social equity are discussed, together with some concepts to reduce inequity.

8.5.1 Network cost recovery

Network costs are driven not by the volume of energy, but by the peak power demand; it is this maximum power flow that determines the rating of transformers and sizes of cables required. Despite this, network costs are recovered from domestic consumers via their electricity supplier through a mixture of unit charges and a fixed daily charge. This can be seen as providing a more equitable cost recovery since more affluent households are likely to consume more electricity, whilst the peak demand is driven by factors often outside the control of the home-owner such as the availability of gas for heating. The introduction of electric vehicles might be considered a change to this paradigm. Exploring the current distribution use of system charges for the Northern Powergrid Yorkshire network area [166] reveals that the base domestic profile employed in the simulation (3,635kWh per annum, noting this is at the high end of OFGEMs UK averages for various consumers [171]) would attract a fixed annual charge of £14.93 per annum with a variable component of £41.19, giving an annual unit cost equivalent of 1.54p kWh^{-1}. The average car owner consumes an additional 1,835kWh, creating a total variable cost of £61.98 or an equivalent annual unit cost of 1.41p kWh^{-1}. Thus non-car owners are paying ca. 10% more per unit despite contributing less to peak system demand than BEV owners. Whilst demands from BEVs are expected to be manageable within existing capacity for sometime, smart charging and/or additional network investment will be required in some areas in the future. Given the lower levels of car ownership amongst lower income groups and their tendency to drive fewer miles, resulting in greater demand diversification and reduced network impacts, simply spreading the cost of additional network investment evenly across consumers will inevitably lead to greater social inequity.

Thus it will be important to consider future network cost recovery strategies in this context. This might, for example, mean a shift to more demand-based tariffs to incentivise EV owners to shift their charging to lower demand periods and reduce the need for network reinforcement or, where necessary, recover the cost from those most responsible. Cost recovery strategies do, however, need to consider the bigger picture in respect of UK system generation and demand and are discussed further in Section 8.5.3. Another means to level-up costs for car drivers is to provide access to local charging provision at tariffs closer to those available for home chargers; this is explored in the following section.

8.5.2 EV charging and tariff access

Specialist EV tariffs have already entered the market; mostly these comprise relatively simple ToU approaches that, whilst favoured by consumers for their simplicity, do not present a viable long term solution. Currently, these tariffs are helping to ensure that EV charging is not superimposed on the existing domestic peak, but they further contribute to social inequity since they are often unavailable to lower income groups with reduced access to home charging.

Figure 8.27 illustrates how the provision of access to local charging with home-charging 'controlled' tariffs affects the operating costs of three groups; *Constrained City* and *Multicultural Mets*, who have lower access to home charging, and *Suburbanites* with already high access to home charging (similar to *Rural Residents*). This access does, of itself, cause changes in car adoption, which accounts for some of the variation, but also leads to lower operating costs for the *Constrained City*

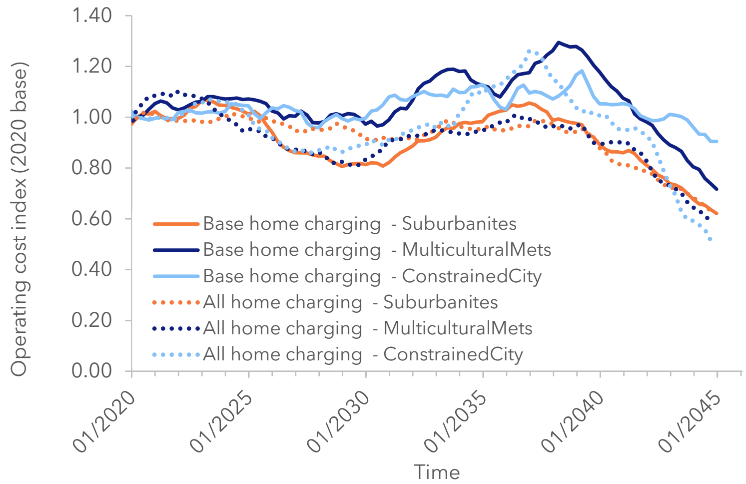


Figure 8.27: Comparison of operating cost index where home charging (or equivalent) is provided for all households

demographic; our lower income group.

Clearly delivering charging to every household is not possible since not all car owners are able to park adjacent to their home. However, there are technological solutions to this. One such solution would entail linking street/car park chargers to drivers' home meters via the meter MPAN (unique identifier), see Figure 8.28. Provided that the charge point is within the same grid area as the householder, this would not present any market reconciliation challenges. In principle, the charger could also allow bi-directional power flow to enable V2H or V2G services. The current EV communications protocols (SAE J2847/1 and IEC 63110) already provide for vehicle identification and automated billing. However, the UK minimum standard for smart chargers [232] does not require implementation of the full Power Line Communications (PLC) protocol, but rather more limited communications that do not provide for the charger to identify the vehicle or its current SoC (more accurately estimated range or kWh stored), both of which are critical to managing vehicle charging and virtual billing.

Installation of street/public chargers incurs a cost and is currently being undertaken by a mixture of local authorities and private entities. These costs need to be recovered by the provider and so it is unlikely to be possible to match the benefits from home charging. It is, of course, also true that installation of a home charger incurs cost; typically around £1,000 [43], although in future these are likely to be treated as household fixtures in regard to property purchases. Assuming an

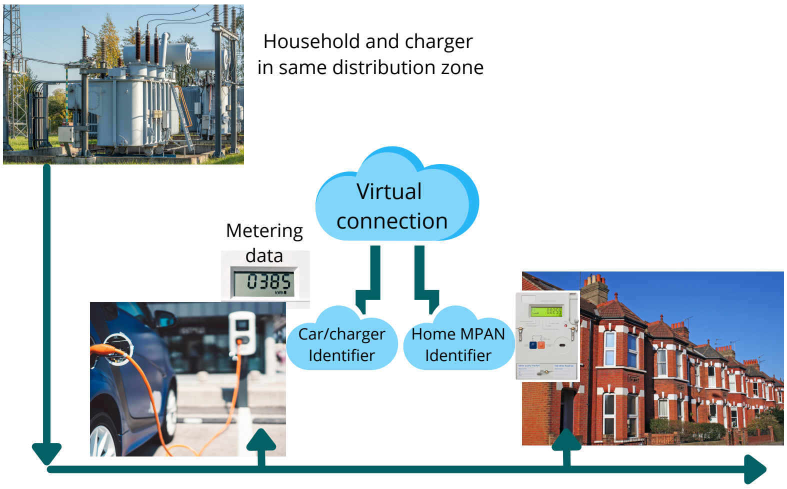


Figure 8.28: Virtual meter equivalence could allow EV owners without home charging to have access to the same opportunities as those with.

average public 7.2kW charging cost of 25p kWh^{-1} and home charging at 7.0p kWh^{-1}, with annual use of 1,385kWh, the simple payback on a home charger is four years, although with more specialist EV tariffs and/or access to home solar (which could also be enabled by virtual metering), this can be reduced to around 2 years. Given the broader benefits to society that smart-enabled public charging such as this could bring (i.e. reduced electricity system costs in addition to more equitable charging provision), there is a significant argument to be made for these chargers to be provided as a public good. However, it is unlikely that there could be sufficient chargers available at all times for all users (meaning that it is not strictly 'non-rivalry' under the definition of a public good). As such, a charge for time connected may be appropriate, or a charging scheme that provides a limited number of hours per week per vehicle.

Going beyond simple charging provision to consider V2G, requires consumers to have longer duration access to a connection to take advantages of periods of high and low renewable generation output. Providing this access is potentially important from a electricity system management perspective as well as a means to reduce inequity in charging. Figure 8.29 illustrates how the operating cost index for the *Constrained City* group, with low access to home charging, varies with differing V2G access scenarios. A feature here is that it is not necessary to provide home-equivalent charging access. That is, provision of charging on average twice per week provides the same benefit as having home charger access at all times. There is, however, a marginal cost benefit to having additional access to V2G

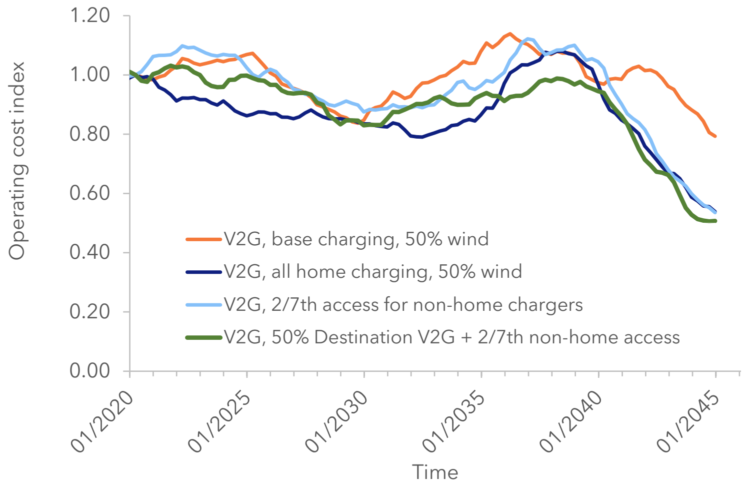


Figure 8.29: Comparison of operating cost index for various V2G options for the *Constrained City* group. Note that V2G import and export tariff is assumed to be the off-peak tariff.

services at destination locations. Since the tariff used for V2G is the off-peak tariff for both import and export, (i.e. there is no consumer cost benefit to V2G itself in the current simulation) it is also possible to conclude that the same level of access without V2G is sufficient to provide more equitable charging costs.

8.5.3 Broader system challenges and pricing models

In the current UK electricity market, wholesale prices are largely driven by the cost of gas since this is the marginal generation type. Intermittent renewables, such as wind and solar, which are likely to dominate UK generation in the future, have close to zero marginal cost [58], so it is likely that wholesale costs will be more volatile. Low costs can be expected at times of high renewables generation and potentially very high costs when renewables generation is low. Currently, wholesale prices are not visible to domestic consumers; it is one role of suppliers to manage these cost risks and deliver a predictable consumer price. However, if the potential of EVs to manage system demands, either through smart charging or full V2G, is to be realised, then there will be a need for greater price visibility at consumer level. This has the potential to see much higher differentials between low and high cost periods; the Covid pandemic provided an insight into what may happen in such circumstances since demands were low compared to renewables generation. The result was a number of low demand periods when EV drivers using the Octopus Energy Agile tariff, which mirrors wholesale prices, were paid to charge their cars [113]. With higher range EVs only requiring a recharge once a week, those with flexible access to charging have the potential for very low, even negative, operating costs, whilst those unable to choose when they charge may experience very high pricing. A further complication comes in that price signals at the wholesale market level may not reflect the needs within the final distribution system. That is, high renewables output at UK-level might drive pricing that encourages significant EV demand which causes local networks to become overloaded.

It is, however, important that pricing mechanisms do not discourage EV owners from participating in supply/demand balancing activity; indeed it is likely that the benefits will need to be quite substantial to encourage this behaviour. Thus a future charging structure should combine demand charges and flexible tariffs. Those EV home chargers unwilling to shift demand to support the grid, and who remain on flat unit-charge arrangements, would then see an increase in demand charges. Counterbalancing the market's need for a complex tariff structure to ensure generation and demand is balanced appropriately against system constraints is the need to to provide clarity and simplicity for the bulk of consumers. It is evident from other market sectors that the majority of consumers prefer simplicity and are, perhaps, prepared to pay for it. For example, 'mobile bundles' offering a fixed monthly payment including the phone, but also data allowances and texts etc. are known to be more popular when the upfront element of the cost is reduced in favour of higher monthly payments or longer terms and consumers appear to lack the knowledge of data use by different applications to make an informed choice on data allowances, with average US contracts providing twice the allowance actually used by consumers [69]. In practice then, the tariffs appropriate to consumers may not align with those needed by the industry, so suppliers will continue to manage market risk on behalf of consumers. Alternatively, other service providers (frequently known in today's market as aggregators) could step in to bridge the gap, managing EV charging and discharging across a fleet of vehicles to deliver the required demand pattern to suppliers and desired charge level to consumers. With the expected increase in volatility of wholesale prices and likelihood of more network constraints, more direct control of consumer loads will be required to reduce the risk margin consumers pay and ultimately the need for system reinforcement and static battery storage. Outlined in the bullets below are a series of key features of tariffs, and where relevant, associated policies that considered necessary to deliver an equitable EV charging environment that simultaneously delivers on both the country-wide and local requirements of a future grid powered by a high proportion of intermittent renewables.

- Local network demand-based ToU charging (a fully-dynamic system is probably not necessary given the relatively slow changes in generation and demand patterns)
- Wholesale pricing visibility at low-voltage consumers (typically managed by suppliers, but available to other service providers, to promote innovation).
- Access to smart charging for all EV owners. This needs to be for a minimum of 7 hours per week to meet average energy use, but to enable smart charging and matching to available generation, and to accommodate higher mileage drivers, the equivalent of two days (which could include daytime destination charging) is likely to be required.
- Development and adoption of the necessary standards to permit V2G and similar services over standard type-2 connections. This must include protocols to to read vehicle's stored energy or estimated range.
- 'Open access' public chargers that enable smart assignment of charging costs and benefits.
- Virtual MPAN assignment, or equivalent, to enable non-home chargers to access at least some benefits available to home chargers.

8.6 Conclusions

In this section, an assessment of the likely size of batteries and stored energy available to the system has been presented alongside indicative impacts on demand in various locations and social groups. A heuristic V2G algorithm has been explored to identify the impacts of such technology on those same social groups and locales and at the broader system level.

From a technical perspective, it is apparent that different social groups, often associated with geographical areas, will have very different consequences for demand profiles. It emerges that *Rural Residents* are likely to present the most challenging group whilst *Hard Pressed* city residents have the least impact. Without appropriate charging controls whether that be smart charging or a more comprehensive V2G arrangement, network impacts will be significant at high penetrations and network reinforcement will be required in rural, and probably suburban, areas. Without modification, the cost recovery mechanisms for this investment will fall disproportionately on less wealthy groups and those, who are not responsible for its need. These same groups will also face higher operating costs for their BEVs unless charging infrastructure is provided in such a manner as to enable access to home-equivalent tariffs.

The analysis shows that V2G can provide a useful benefit both at national and local level, although adoption levels are uncertain and will play a crucial role in its impact. It is also apparent that smart charging alone can deliver a proportion of the benefits of V2G and pay be a more palatable option for consumers. Since both V2G and smart charging also provides the potential for lower operating costs, mechanisms to make this available to the lowest income groups should be a priority. Indeed, it is perhaps these groups who are most likely to participate in V2G and smart services since, on average, their cars could be connected for more of the time, due to lower mileage, and they maybe more willing to participate to reduce their costs.

To facilitate these opportunities, appropriate electricity pricing models are required and, critically, access to chargers enabled to provide the services.

One way to manage demands in rural locations, and to provide charging opportunities for others without home-charging, is to provide a "Park and Ride" facility with charging provision. Such a facility would provide a transport interchange to low carbon-vehicles for the final leg of city commutes, but could equally provide the same service for those seeking access to the countryside. The potential for such a facility is explored in Chapter 9.

Chapter 9

REVIT results and discussion

This chapter presents results from the REVIT bus commuter hub model, based on the case study set out in Section 6.1. There are three questions to which answers are sought through this modelling:

1. To what extent can a renewable-energy powered commuter hub deliver self-sufficiency in transport energy needs?

2. Can such a hub present a viable financial model for future deployment?

3. Can a hub 'Park and Charge' scheme deliver greater social equality in charging costs for those without access to home charging?

The analysis presented includes a number of sensitivity analyses and partial optimisations as well as a set of modelled scenarios. The base scenario is with 2 x 500kW wind turbines plus 700kWp (2kWp x 50 parking spaces) of solar PV. The minimum storage capacities are a 1,000kWh battery and 2,000kg of hydrogen storage. The minimum battery storage was selected due to the current high cost of such systems, whilst the hydrogen storage was chosen based on a hydrogen delivery vehicle carrying 900kg [30] of hydrogen, thus ensuring that there is always adequate volume to offload a full tanker, whilst retaining sufficient reserve volume. However, the scenarios analysed consider storage as a function of days of energy demand for the worst day (the coldest day with longest route-km). For all-electric options this is 4,757kWh and for hydrogen the maximum use on any single day is 206kg. Scenarios are abbreviated as follows, for non-mixed bus types:

- Initial letter indicates bus type (E=electric, H=hydrogen)

- Number indicates storage size in days of mean use for that type

- Changes to base generation/production, where S2 would be 2 Megawatts peak installed capacity (MWp) of solar, W4 would be 4MW of wind and E2 would be 2 x 21.8kg s^{-1} electrolyser units.

For mixed buses the initial section comprises M followed by the initial bus type and number. e.g. MH8 indicates that the model will start with 8 hydrogen buses and add only electric buses as needed to complete the routes.

9.1 Self-sufficiency

To what extent can a renewable-energy powered commuter hub deliver self-sufficiency in transport energy needs?

The ability of a future transport system to be self-sufficient in energy will be a function of the magnitude and types of renewable energy plant installed, the bus mileage and fuel types, whether hydrogen or electric, and the capacity of battery and/or hydrogen storage. For this case-study, self-sufficiency analysis is conducted over the full 4 year period for which wind data was available; only 2 years of solar data (which match two of the wind years) were available; these were repeated.

9.1.1 Wind/solar ratio

Figure 9.1 illustrates how self-sufficiency varies with increasing solar PV capacity, with wind held constant at the base 1MW. The rapid increase in initial self-sufficiency for hydrogen buses is attributable to increased operating hours for the electrolyser. The minimum electrolyser load is 283kW and the model requires 10% excess to start the electrolyser (to avoid rapid start/stop sequences), thus when wind generation is zero, the solar output must be over 311kW to run the electrolyser. Conversely, the electric buses can offer relatively high self-sufficiency with low quantities of PV since the system can always store and make later use of any excess generation. However, the all-electric option is overtaken by the hydrogen scenario because of the large amount of storage available; the base model has nearly 20 days of hydrogen storage vs. 1 day of electricity storage

Electric bus analysis

Figure 9.2 shows how the self-sufficiency of electric bus options varies with increasing central battery storage for three different PV options. The chart illustrates that there is effectively a choice between investing in more solar or more battery

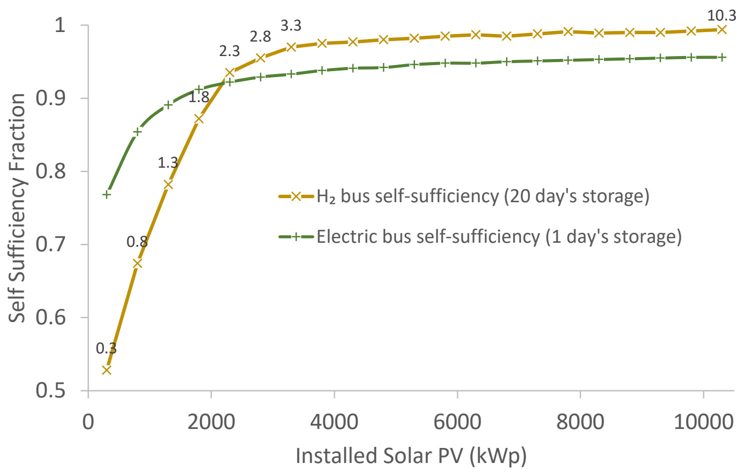


Figure 9.1: Sensitivity of self-sufficiency to installed PV capacity with wind held constant at 1MW. (1 day electricity storage, 20 days hydrogen storage.) Numbers adjacent to curve indicate the ratio of solar to wind (installed capacity).

capacity, but given the relatively high cost of batteries, greater installed generation is likely to be the desired solution where practical (see Section 9.2.1). Assuming efficient mono-crystalline PV systems, a 1.5MWp system would occupy an area of approximately 25,000m^2. This is unlikely to be possible for more urban bus depot locations, but only represents parking for about 750 cars, which is less than half the number at Nottingham's PnR sites [178]. This raises the question as to the viability of solar-only hubs since inclusion of wind may be problematic in many locations and wind resource may not be as good as may be encountered for the 'edge of Peak District' case study presented here.

Hydrogen bus analysis

As noted in Section 9.1.1, hydrogen solutions struggle to reach self-sufficiency without significant additional generation. Figure 9.3 shows that a combination of high generation, 1MW wind and 3MWp PV, combined with 18 days of storage is required to reach greater than 99% self-sufficiency compared to 1.5MWp PV and 4 days of battery storage. The cost of this battery system and PV combination is £4.90M compared to £2.41M for the storage and PV combination for hydrogen buses. However, the electrolyser adds an additional cost of £1.96M, bringing the total cost to £4.37M. Hydrogen buses are also more expensive than their electric counterparts and as such, the cost of self-sufficient hydrogen solutions is always

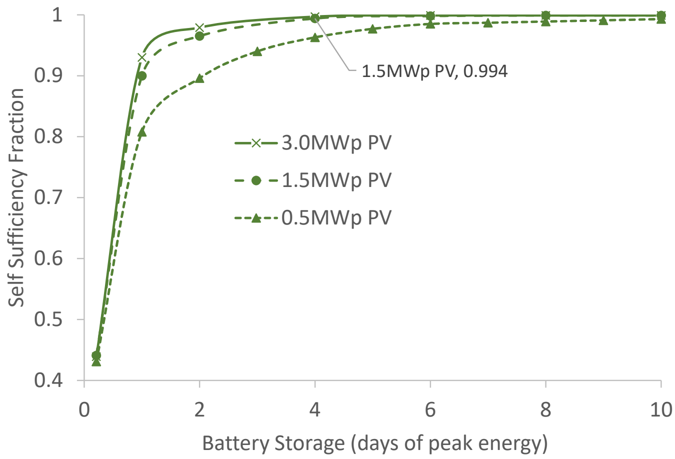


Figure 9.2: Sensitivity of self-sufficiency to installed battery energy capacity (C-rate = 2 in all cases) for three different peak solar capacities with wind held constant at 1MW.

greater.

Impact of electrolyser parasitic demand Adding more generation is beneficial since there will be longer periods where generation is greater than the minimum. However, with a maximum rating of ca. 1.3MW, the electrolyser cannot always take advantage of the extra generation. This can be resolved by adding additional electrolyser units, but here the importance of electrolyser parasitic demand is revealed. Figure 9.4, illustrates how switching from an assumption of 30kW fixed parasitic demand in total [B] to 30kW per electrolyser unit [C] impacts on self-sufficiency where two electrolysers are employed. Referring to Figure 9.5, it can be seen that 30kW represents 30% of the mean winter month's output for a 1MWp array and, consequently, including the extra electrolyser has no positive benefit on self-sufficiency until some 8MWp of solar PV is installed (compare [A] to [C]). (Note that, due to the calculation methodology for self-sufficiency of hydrogen fleets, the figure can become negative due to hydrogen imports - see Section 5.8.) Where on-site wind generation is available, self-sufficiency can be reached at a little over 2MW of solar. Interestingly, adding a second electrolyser makes this system less self-sufficient due to periods when there is no generation, but greater fixed parasitic demand. This analysis indicates that careful selection of electrolyser size and control of electrolyser operation, perhaps involving a greater degree

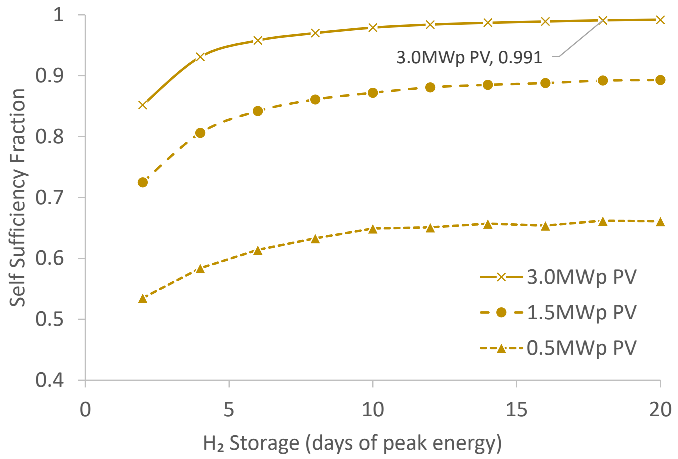


Figure 9.3: Sensitivity of self-sufficiency to hydrogen storage capacity for three different peak solar capacities with wind held constant at 1MW and with a single electrolyser unit.

of system shutdown when not in service to reduce parasitic demand, is essential to deliver the optimum outcome.

Solar-only hub performance

Figure 9.6 illustrates the sensitivity to storage duration with solar, but no wind generation for electric buses. This shows that battery storage has a significant impact up to around 2 days of peak energy capacity, but beyond this the benefits result in only a marginal increase. In the extreme case, a 120 day battery (570,883kWh at an estimated cost of £111M) combined with 2.5MW of solar would deliver a self-sufficiency of 98.9%.

Figure 9.4 [A] and [C], show results for a single electrolyser and two electrolyser solution with PV-only generation and show clearly that hydrogen bus scenarios need high levels of generation to achieve the same self-sufficiency as electric solutions; with only 2 days of storage, the electric bus solution can deliver over 80% self-sufficiency with 5MWp of solar, whereas this is only reached for the hydrogen bus solution at around 10MWp of solar. Furthermore, the hydrogen option also requires additional electrolyser capacity, operating with a low capacity factor, to take advantage of the short periods of high generation in the middle of the day. One option to overcome this would be to provide a parallel battery storage system that can accumulate small amounts of solar generation until there is sufficient to

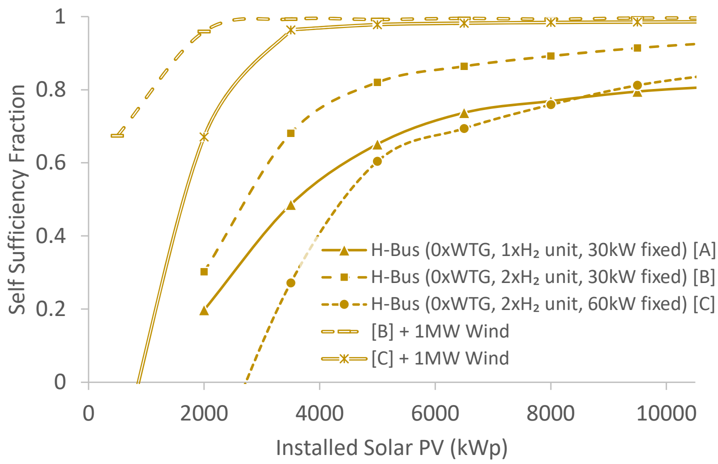
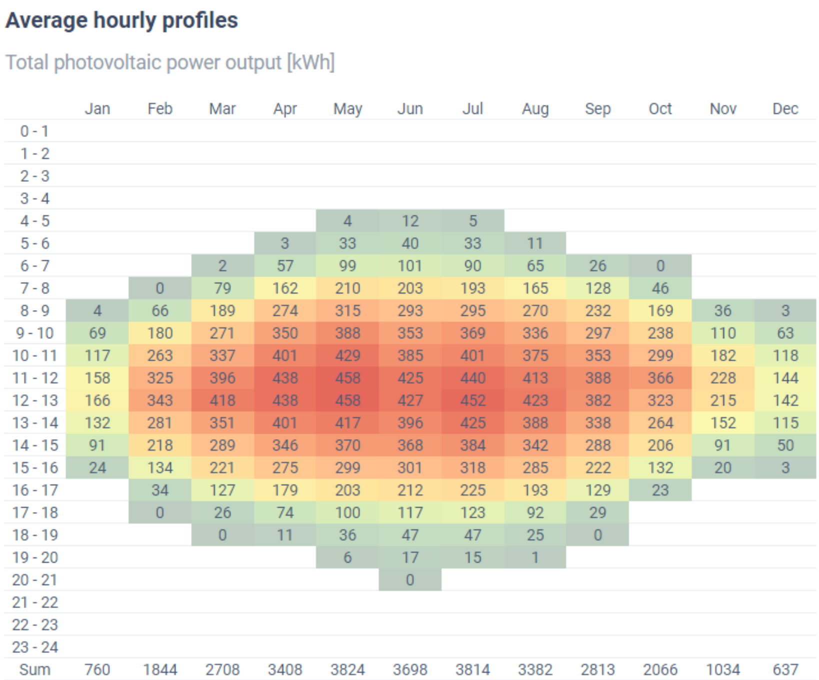


Figure 9.4: Sensitivity of self-sufficiency to installed solar capacity with either 0MW or 1MW wind generation, showing the impact of parasitic demand.



Average hourly profiles

Total photovoltaic power output [kWh]

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0 - 1												
1 - 2												
2 - 3												
3 - 4												
4 - 5					4	12	5					
5 - 6				3	33	40	33	11				
6 - 7			2	57	99	101	90	65	26	0		
7 - 8		0	79	162	210	203	193	165	128	46		
8 - 9	4	66	189	274	315	293	295	270	232	169	36	3
9 - 10	69	180	271	350	388	353	369	336	297	238	110	63
10 - 11	117	263	337	401	429	385	401	375	353	299	182	118
11 - 12	158	325	396	438	458	425	440	413	388	366	228	144
12 - 13	166	343	418	438	458	427	452	423	382	323	215	142
13 - 14	132	281	351	401	417	396	425	388	338	264	152	115
14 - 15	91	218	289	346	370	368	384	342	288	206	91	50
15 - 16	24	134	221	275	299	301	318	285	222	132	20	3
16 - 17		34	127	179	203	212	225	193	129	23		
17 - 18		0	26	74	100	117	123	92	29			
18 - 19			0	11	36	47	47	25	0			
19 - 20					6	17	15	1				
20 - 21						0						
21 - 22												
22 - 23												
23 - 24												
Sum	760	1844	2708	3408	3824	3698	3814	3382	2813	2066	1034	637

Figure 9.5: Variability of solar output over an average year for a Chesterfield location, 1MWp array. Source: Global Solar Atlas [238]

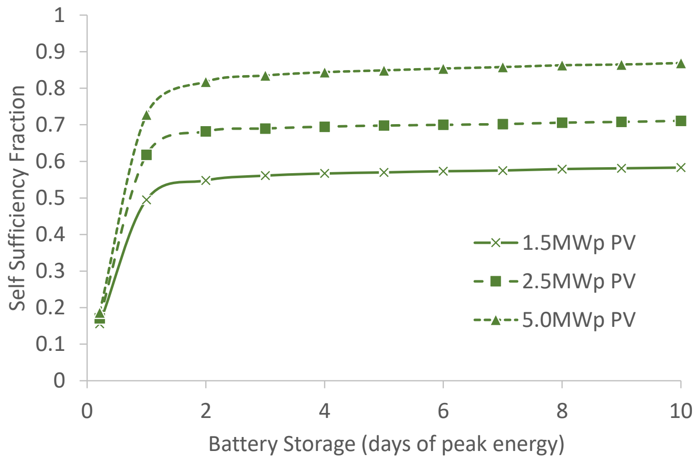


Figure 9.6: Sensitivity of self-sufficiency to battery capacity for three different PV array sizes for an all-electric bus, PV-only solution.

run the electrolyser for a few hours. Generating one day of hydrogen demand, requires ca. 12MWh of electricity. Figure 9.5 shows that over the three lowest PV output months, this requires an average of ca. 15 days of production at 1MWp solar. 5MWp of solar would require ca. 2 days of electricity storage (assuming some direct solar charging occurs) to achieve 1 day of hydrogen consumption; this same storage/PV capacity can deliver around 80% self-sufficiency for a fully electric bus fleet. Thus whilst an onsite battery could support greater self-sufficiency in hydrogen, it is unlikely that this would present a financially viable solution compared to adopting electric buses.

9.1.2 Optimum self-sufficiency solutions

In general, the model forecasts an improved NPV as generation is increased. This means that attempting to maximise NPV in an optimisation with a minimum self-sufficiency constraint simply results in maximising generation for which, in any practical application, there will be some constraint, whether grid connection capacity, available land area or planning concerns. To overcome this, the optimisation was run with an objective to minimise capital cost subject to achieving a self-sufficiency greater than 95%. This was evaluated separately for all electric solutions and all-hydrogen solutions. The optimisation was carried out using step-wise changes in parameters, and over four years, this was partly to reflect the step-wise nature of some equipment (such as wind and electrolysis plant) but also

Table 9.1: Electric bus optimisation parameters

Parameter	Units	Minimum	Maximum	Step	Optimum
Wind turbine count	Number of 500kW units	0	6	1	2
Solar PV Capacity	kWp	500	5000	500	1500
Electricity Storage	Days of Maximum Demand	0	10	1	2

to reduce execution time to an acceptable level (around 12 hours). The optimised parameters were then used in a full 12-year simulation to generate a bus-lifetime NPV.

All-electric bus solution

The all electric bus optimisation was set up using the parameters in Table 9.1, which also shows the optimum values found. This solution results in a capital cost of £11.98M, a self-sufficiency of 96.6% and a 12-year NPV of -£9.12M.

All-hydrogen bus solution

The all hydrogen bus optimisation was set up using the parameters in Table 9.2, which also shows the optimum values found. This solution results in a capital cost of £12.66M, a self-sufficiency of 95.9% and a 12-year NPV of -£11.63M. Interestingly, the solution includes two electrolysers, which may, in practice, be essential anyway to ensure reliability of supply. The lead electrolyser operates for an average of 4,741 hours per year with a capacity factor of 33.8%, whilst the second electrolyser operates for only 335 hours per year with a capacity factor of only 2.1%. Reducing to a single electrolyser unit results in a self-sufficiency of 92.2%. This indicates that a more optimal solution may be found with two lower output electrolysers; testing this with $2 \times 15\text{kg h}^{-1}$ (as opposed to $2 \times 21.8\text{kg h}^{-1}$) gives a self-sufficiency of 95.3% with lead and secondary electrolyser capacity factors of 45.1% and 7.4% respectively (5,380 and 1,028 operating hours per year for the lead and secondary units respectively). Assuming a linear decrease in capital cost per unit output for the electrolyser, the total CAPEX would reduce to £12.05M.

Hydrogen vs electric comparison

The CAPEX optimisation here illustrates fairly clearly the challenges of each solution in delivering self-sufficiency. Whilst the all-electric bus solution requires

Table 9.2: hydrogen bus optimisation parameters

Parameter	Units	Minimum	Maximum	Step	Optimum
Wind turbine count	Number of 500kW units	0	6	1	2
Solar PV Capacity	kWp	500	5000	500	2000
Hydrogen Storage	Days of Maximum Demand	10	120	10	40
Electrolyser Units	Number of $21.8kgh^{-1}$ units	1	2	1	2

substantially less primary energy, the high cost of battery technology enforces a relatively high base of installed renewable capacity, about 50% of which is either spilled to the grid or used to charge cars at the hub. In the hydrogen solution, whilst requiring some 2.8 times as much primary energy, the total installed renewable capacity is only a factor of 1.2 greater than the all-electric CAPEX optimised solution. This is because of the much lower cost of hydrogen storage, with 40 days included in the optimised solution compared to just 2 days of electricity storage. Despite this, the high cost of hydrogen buses compared to electric buses and the additional revenues available from the excess power render the electric bus option more economically viable as discussed in Section 9.2

9.2 Economic Viability

Can such a hub present a viable financial model for future deployment?

In this section, a comparison of the financial viability of various scenarios is presented. Since the model does not incorporate travel fares or parking charges (or indeed some costs such as labour and management overheads), NPVs for all options are negative. However, these costs and revenues are likely to be very similar across all scenarios, thus it is reasonable to consider the relative magnitude of NPVs rather than absolute values.

9.2.1 Impact of storage volumes on NPV

Before introducing the scenarios, it is worth considering the relative impacts of electric and hydrogen storage on NPV. Figure 9.7 illustrates how adding storage volume to the base scenario for two different PV capacities impacts on all-hydrogen and all-electric bus options. The chart clearly shows that, with its relatively low cost, additional hydrogen storage increases NPV whilst the high cost of battery storage always reduces the NPV. That is, the benefits of arbitrage between

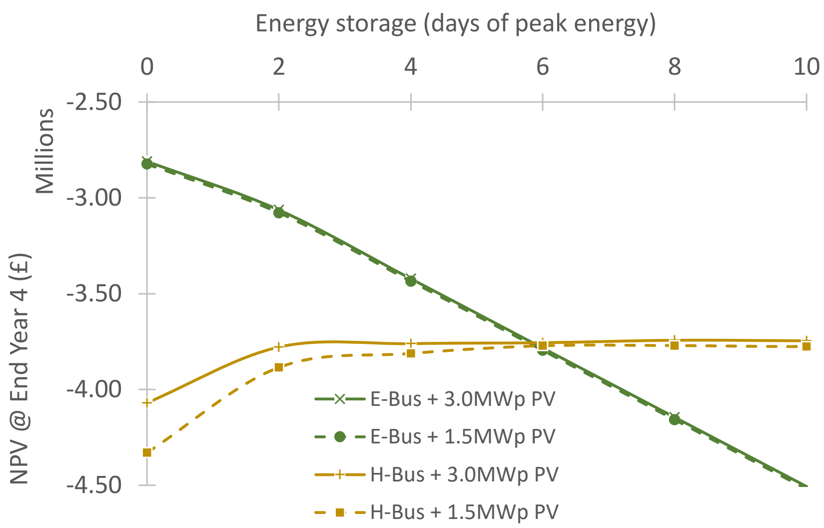


Figure 9.7: Impact of storage capacity on NPV

off-peak and peak power prices and the relative value of exports at those times do not merit the additional cost of electricity storage. However, in the future, one might reasonably expect that wholesale electricity prices (to which a customer of this nature may choose to be exposed) are more likely to be related to the volume of renewable generation. When close-to-zero marginal cost renewables are able to supply all demand, then wholesale prices are likely to be low, whilst at times of low renewable generation, when some form of stored renewable energy is being used, prices will be high. Thus, a renewable energy powered hub such as this would likely experience much higher import costs at times of its own low generation and therefore benefit more from storage ownership. It is not unreasonable to speculate that the value of electricity storage may, at some future point, represent a worthwhile investment. With bus batteries expected to last around 6 years (to 70% SoH), there is clearly an opportunity for a second-life application within the bus hub; not only would such batteries be available at low capital cost, but also in that time frame, wholesale price changes may make them more viable.

9.2.2 Scenario financial performance

Table 9.3 presents the selection of scenarios for which a full 12 year analysis has been conducted; 12 years was chosen as this is the anticipated lifetime of the buses [210]. The scenarios include the base case of 2 wind turbines plus solar on all

Table 9.3: Scenarios for financial modelling

Scenario Name	Code	Hydrogen buses	Electric buses	Wind capacity kW	Solar capacity kW	Electrolysers 21.8kg s^{-1} Units	Hydrogen storage Days	Electricity storage Days	Charging spaces
Diesel reference	D0W0	0	0	0	700	0	0	0	125
Hydrogen bus scenarios									
Base hydrogen	H20	15	0	1000	700	1	20	0	125
CAPEX optimised hydrogen	H40W1S2P2	15	0	1000	2000	2	40	0	125
High renewables hydrogen	H60W2S5P2	15	0	2000	5000	2	60	0	125
Base solar-only hydrogen	H40W0	15	0	0	700	1	40	0	125
Electric bus scenarios									
Base electric	E1	0	18	1000	700	0	0	1	125
High storage electric	E4	0	18	1000	700	0	0	2	125
CAPEX optimised electric	E2W1S1.5	0	18	1000	1500	0	0	2	125
High renewables electric	E2W2S5	0	18	2000	5000	0	0	2	125
Base solar-only electric	E2W0	0	18	0	700	0	0	1	125
Mixed bus scenarios									
Low hydrogen mix	MH4	4	Model	1000	700	1	20	1	125
Mid hydrogen mix	MH8	8	Model	1000	700	1	20	1	125
High hydrogen mix	MH12	12	Model	1000	700	1	20	1	125

parking spaces for all-electric (E1), all-hydrogen (H20) and various combinations of buses (MH4/8/12). The optimised lowest capital cost solutions (H40W1S2P2, E2W1S1.5) together with high renewables solutions (H60W2S5P2, E2W2S5) are also included. An additional electric-only solution with 4 days of storage (E4) is considered as this duration appears to offer close to maximum self-sufficiency without entailing excessive capacity. A solar-only scenario for electric (E2W0) and hydrogen (H40W0) options is shown, based on only that solar which could be accommodated within the hub parking area in the form of parking canopies. An additional ’Diesel’ bus case (D0W0) is included for reference. This case includes the provision of car charging so that the capital and maintenance costs of car chargers are consistent across all scenarios.

Since the model excludes costs and revenues that would likely be identical across all scenarios, namely labour and overhead costs and fare and parking revenues, the results are presented as variation from the mean of all scenarios.

Figure 9.8 shows the NPV of each scenario relative to the mean of all scenarios. The business-as-usual diesel case still represents the lowest cost option at the current time; this accords with a 2020 study by Jefferies [119], which shows the total cost of ownership for diesel buses to be 1.35€ km^{-1} compared to 1.90€ km $^{-1}$ to 2.14€ km^{-1} for various electric bus strategies. The most striking feature is the relatively poor performance of hydrogen buses, with all scenarios incorporating them faring worse than the mean. This is largely caused by the high capital cost of the buses themselves; £525k per unit compared to £400k for electric and £200k for diesel. The total capital cost for the base hydrogen option is £11.6M compared to £10.4M for the base electric option, despite the need for three additional elec-

Table 9.4: Bus counts and storage sizes for mixed scenarios

Scenario Name	Code	Hydrogen buses	Hydrogen storage kg	Hydrogen storage £	Electric buses	Electricity storage kWh	Electricity storage £
Low hydrogen Mix	MH4	4	1,532	3,064	13	2,931	571,648
Mid hydrogen Mix	MH8	8	2,802	5,604	9	1,438	280,556
High hydrogen Mix	MH12	12	3,846	7,692	4	1,000	195,000

tric buses. Two of these buses are purchased in year 2 and year 5 as a result of battery degradation; a more sophisticated scheduling algorithm may well be able to make use of these buses as spare units that, in practice, are required for maintenance/breakdown unavailability. This option is not available in the hydrogen scenarios, thus requiring additional spare buses and resulting in an even worse financial performance.

The mixed bus scenarios do not appear to offer any significant benefits with the routes modelled here; this may different in other cases where there are longer routes that cannot be completed with pure-electric options. The storage volumes for these scenarios are based on 1 day of electricity storage and 20 days of hydrogen storage and therefore vary between scenarios as illustrated in Table 9.4; the 1,000kWh store in the high hydrogen mix is the default minimum size. The electricity storage size variations are a key factor in determining the NPV, alongside the cost of hydrogen buses.

With grants available for zero-emission buses [225], operational costs are of significant interest to local authorities, since the full CAPEX of the solution may not be incurred. Figure 9.9 sets out the net cost of energy for each scenario, i.e. the cost of imported energy (or fuel in the case of diesel) less the value of exported energy. This clearly shows that, with the exception of the solar-only hydrogen option, zero-emission scenarios have lower energy operating costs than the base diesel option. Furthermore, all electric options (apart from car park only solar, E2W0) deliver net operating revenues from energy surplus and car charging. For hydrogen bus solutions, the only net positive revenue option is that with very high on-site renewable generation.

9.2.3 Self-sufficiency and carbon emissions

Figure 9.10 illustrates the self-sufficiency fraction for each of the options, essentially reconfirming earlier analysis and a preference for electric bus solutions with relatively low storage to achieve high levels of self-sufficiency.

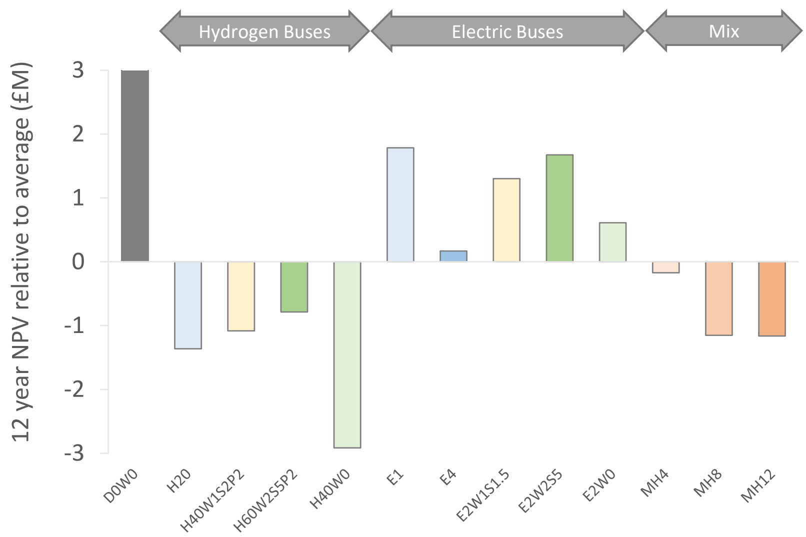


Figure 9.8: 12 year Net Present Value of scenarios at 3% discount rate, expressed relative to the mean of all scenarios

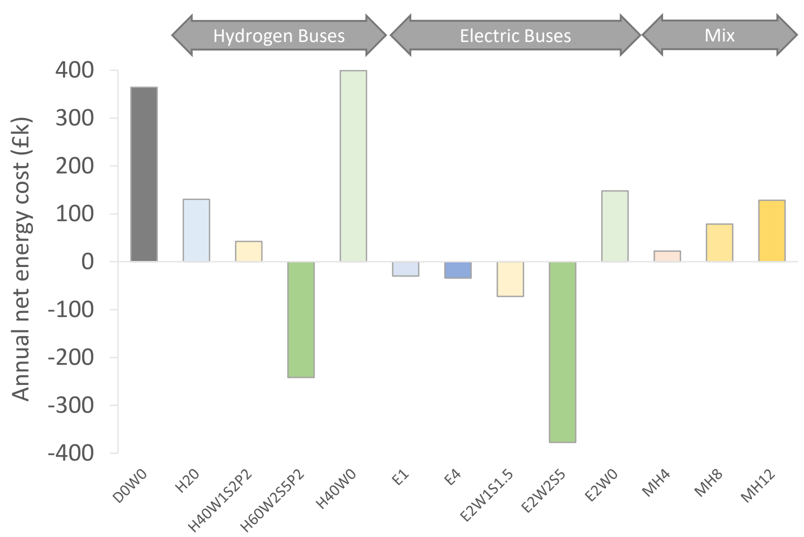


Figure 9.9: Annual net energy operating costs for all scenarios

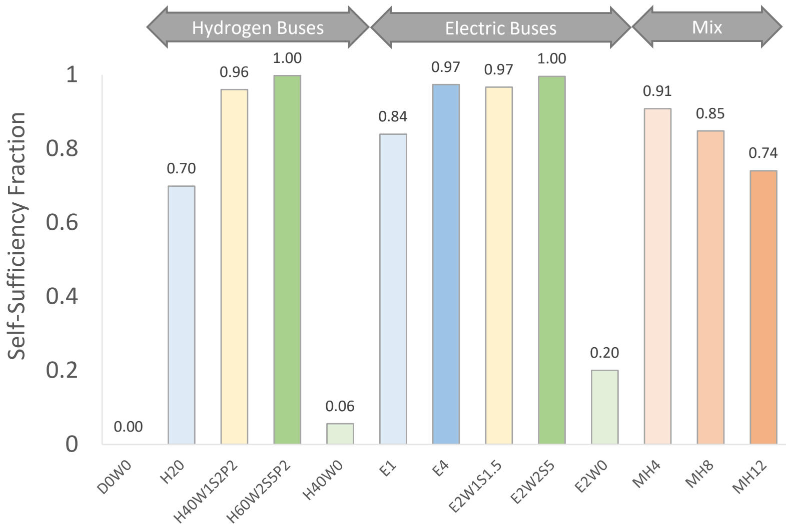


Figure 9.10: Self-sufficiency of modelled scenarios

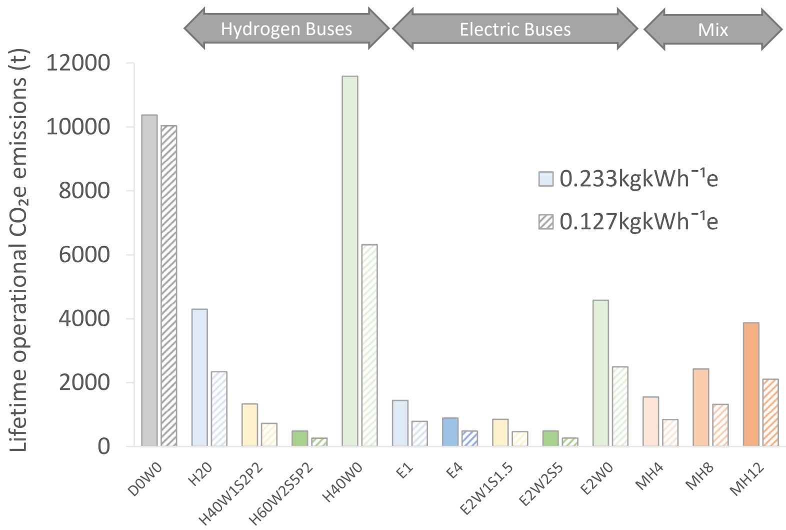


Figure 9.11: Lifetime operational carbon emissions of modelled scenarios

Figure 9.11, sets out the 12-year lifetime operational carbon emissions (excluding embodied carbon) based on 2020 UK grid emissions and average biofuel-blend diesel [222] and a forecast for grid mean emissions over the next 12 years of 0.127kg $kWh^{-1}e$ (see Section 3.2.3). At the current electricity emissions factor, hydrogen buses result in higher carbon emissions than diesel buses, but with declining power sector emissions over the 12 year bus life, the actual lifetime emissions are expected to be 38% lower than that of the diesel base case. Note that the diesel case shows a slight decline in emissions under the different grid factor scenarios because car charging is included in the evaluation. Electric bus options present consistently lower and earlier benefits compared to hydrogen bus scenarios except where large amounts of on-site renewables can be accommodated. An alternative strategy would be to procure renewable energy from the grid, supported by the necessary certification, which would effectively make all options, other than diesel, carbon neutral from an operational perspective. Adding a carbon cost of just 2.00£ tCO_2^{-1} to diesel (not to electricity imports) is sufficient to deliver the same NPV for option E1 as the diesel base option.

9.3 Social equity benefits

> Can a hub 'Park and Charge' scheme deliver greater social equality in charging costs for those without access to home charging?

The BEVI model has confirmed the potential for social-inequity arising from the availability of home charging. Rapid chargers have high capital costs and may also incur high demand charges, so extending the potential for those without access to home charging to charge their cars at slower, lower cost, chargers, either during the day or overnight, could help address this cost inequity. the commuter hub clearly offers the potential for daytime charging. In fact, although not modelled here, it could also offer overnight charging, with car owners returning home on buses from the hub.

9.3.1 Car charging outcomes

The modelled hub has, on average, 304 cars arriving during the morning commute and 125 parking spaces equipped with chargers. The algorithm used to set the charging price is designed to dissuade those with home charging from connecting by ensuring that the price is likely to be higher than they can obtain at home. The actual cost of charging will depend on installed capacity of generation and types

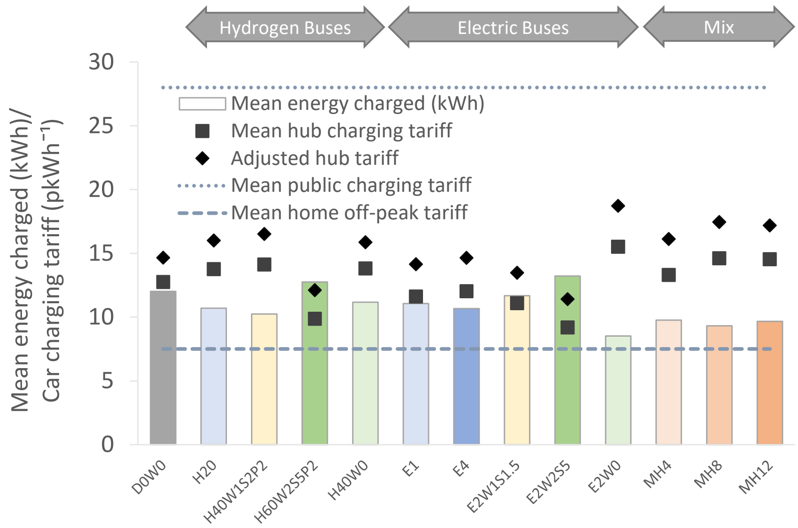


Figure 9.12: Scenario car charging outcomes

of bus used since this will affect the times when export is occurring and thus when prices are at their lowest for car chargers (see Section 5.7.)

Figure 9.12 shows the mean unit tariff for car charging for each of the scenarios modelled and clearly illustrates that the hub is able to offer substantially cheaper charging than public chargers. However, when analysing the charging infrastructure investment as a stand-alone project, the 25% mark-up is found to deliver insufficient revenue to return a positive NPV after 12 years at the base public sector 3% discount rate used in the model. The 'Adjusted hub tariff' series (diamonds) shows the tariff required for each scenario to deliver a 3% IRR at year 12; the mark-ups required vary from 44% to 55%. The reason for the variation in tariffs across scenarios can be attributed to the the volume of surplus power during the periods when cars are parked at the hub and the bus type employed. Where electric buses are used, surplus energy is always prioritised for maintaining central battery SoC and bus rapid charging. This means that, for example, in case E2W0, where there is only a small solar PV system, almost all energy from the panels is used either for bus charging or central battery charging meaning that cars must be charged with imported peak-time electricity; hence incurring a high cost. For the hydrogen solar-only case, the electrolyser cannot always make use of the solar (due to minimum load constraints) and therefore there is some solar available for car charging, resulting in a lower unit price; the diesel base results in the lowest solar-only price since all solar is available for car-charging. Cases with high generation tend to result in lower tariffs due to the mark-up being applied to the lower export tariff rather than the peak-hours import tariff, conversely, this requires a higher percentage mark-up to achieve a constant financial return. Lower tariffs also result in higher volumes charged since more customers will have a compatible price threshold. Whilst these low tariff scenarios tend to result in a higher mark-up, since the mean price is lower (more occasions when the hub is exporting), the resulting tariff remains lower than other cases (H60W2S5P2 and E2W2S5). The mean charging tariffs are also always above the mean home off-peak tariff, indeed, they are broadly inline with normal single-rate (daytime) home tariffs and thus are unlikely to be attractive to those with access to home charge points.

9.3.2 Social equity benefits

It is apparent from the analysis here that the renewable powered hub is able to offer car charging at lower cost than current public charging provision. However, the tariff payable is still around double that available to home chargers. An important consideration here is the capital cost of the home charger unit itself. With an estimated cost of around £1,000 [43], this in itself represents around 40,000km of electric driving at 15p kWh^{-1} (being a reasonable average hub charging tariff). The NPV for home charging at average UK mileage and the average off-peak tariff of 7.5p kWh^{-1} with a £1,000 charger is -£2,965. For a hub user the NPV is -£3,988. To arrive at the same effective cost over 12 years requires a hub tariff of 11.15p kWh^{-1}; only the high renewables scenarios are able to approach this figure.

If local EV drivers could be persuaded to use the hub for overnight charging, and this is optimised around electric bus charging and/or electrolyser operation, then this would potentially increase the utilisation of chargers and thus reduce the tariff needed to achieve the desired return on investment. Such overnight charging would also be at a lower price (under the modelled import tariff scenarios) than average daytime charging.

9.4 REVIT conclusions

The results presented in this chapter show that, for the set of routes and renewable generation modelled, it is possible to achieve high levels of energy self-sufficiency; above 90% being achieved for six of the 12 twelve zero-tailpipe emissions scenarios presented. Hydrogen solutions with low onsite renewable capacity may not offer the optimal carbon benefits unless certified low-carbon grid energy is procured.

At the current time, diesel buses remain the most financially viable option where the cost of carbon emissions is excluded. This may not, however, be the case where emissions permits are required to enter city zones. Electric bus options with on-site generation and low levels of on-site storage are the next best financial option and could be seen as competitive with diesel buses where carbon is costed at a low value of 2.00£ tCO_2^{-1}. Hydrogen buses do not currently present a viable financial option, but there may be technical reasons why such solutions are needed - for example in locations where adequate charging provision cannot be provided. Lord and Palmou [141] note in a policy paper, the need for road pricing to avoid the costs of congestion, which they argue are likely to increase as EVs are adopted due to their lower running costs and consequent increase in attractiveness compared to current public transport services. They identify some £74.9Billion in congestion costs to the UK economy today, with an expectation that could rise to £144.6Billion by 2040. Congestion charging in urban centres with revenues directed at supporting commuter hubs such as this, may be a practical way to alleviate the societal costs of increased congestion. The hub concept does provide the potential to reduce charging costs for those without access to home charging, but it is unlikely to be able to offer rates equivalent to over-night home tariffs.

Chapter 10

Conclusions

This chapter presents a brief review of the achievements the BEVI and REVIT models and brings together the results from all the analysis to draw conclusions on what strategies are most likely to deliver a technically optimal and socially equitable transition to an electric transport system. Finally the limitations of the models and opportunities for future work are dicussed.

10.0.1 BEVI model achievements

The BEVI model has been shown to be accurate at forecasting the historic switch from petrol to diesel and produces a realistic adoption curve for electric vehicles that sits within the range of other forecasts which are typically based on 'top-down', bass-diffusion type, analysis of potential growth rates. The forecast electricity demands at system level have also been shown to match those obtained from real-world charging studies.

Where the work breaks new ground is in the granularity of analysis across different socioeconomic and geographic groups and the ability to explore alternative charging scenarios at half-hourly intervals; essential for determining local network impacts and effects on the electricity market. The policy analysis element also benefits from being able to assess impacts within different socioeconomic groups and to explore how differing strategies may help reduce future inequity in EV adoption and operating costs.

In respect of V2G, the BEVI model is able to explore impacts both at national and local system level simultaneously and how enhancing access to V2G by different socioeconomic groups and at different locations can bring benefits to users, local networks and provide much needed time-shifting of renewable generation at a national scale.

10.0.2 REVIT model achievements

The REVIT model has been shown to give outcomes consistent with the findings of earlier electric and hydrogen bus studies and extends them to explore ideas of self-sufficiency in energy supply and opportunities to support the equitable transition to electric vehicles more generally.

The case study simulation has shown that in an edge-of-town location, high levels of energy self-sufficiency, close to 100%, can be achieved, and that this can be done without compromising financial performance. A new and interesting outcome is that optimisation of vehicle selection may favour uneven use of buses. This presents a potentially new optimisation strategy for fleets which operate on a range of different route lengths and terrains.

This is the first time that the potential of a public transport hub on improving cost equity in EV charging has been demonstrated. The simulation shows that significant benefits can be delivered for those with poor access to home charging.

10.1 Electric vehicles: a fair way to go

This thesis has sought to examine how human behaviour and political influence might impact upon EV adoption and charging approaches, the effects on our electricity systems and related issues of equality across socioeconomic groups. It has explored how EVs can have both negative and positive impacts for our electricity networks and how they might help balance a future system with high levels of wind and solar generation. It has also examined how public transport might be supported by those same renewable energy sources and the potential for bringing together public and personal modes of travel to deliver wider benefits and support an equitable transition. In this section, highlights from the analysis are presented along with thoughts on how policies can be framed to support a fair transition to electric mobility whilst maximising the benefits to future electricity generation and distribution.

10.1.1 Policies for adoption

It is evident that the UK government's current policy of a ban on the sale of ICE vehicles is, of those levers analysed, the most effective. A ban benefits from having almost no immediate or direct cost to the tax payer, although in practice tax benefits to private, company and fleet car owners have also been introduced. Whilst these can be seen as benefiting the higher socioeconomic groups, they do help precipitate the shift to EVs, facilitating higher volume production which brings down costs, and providing a market to encourage the development of charging infrastructure. They also allow the establishment of a used EV market earlier, enabling those on lower incomes to benefit from reduced operating costs sooner. In addition, it is known that emissions from ICE vehicles have a mildly disproportionate effect on the health of those from urban areas and lower socioeconomic groups [188, 211], thus accelerating the transition may have accompanying health benefits. However, the current tax benefits, and indeed capital grants, tend to favour high socioeconomic groups. Thus to maintain an equitable transition, it is appropriate to phase out these benefits as parity with ICE vehicles approaches. This work has also shown that such a strategy is possible with limited impact on EV adoption rates or progress with carbon reduction.

Grant support for charging infrastructure has also been a feature of government policy in the UK and elsewhere. Whilst it is likely that there is much greater diversity in individuals' decision making processes than it is possible to simulate, the heuristic algorithm introduced here is able to test the impacts of charger deployment and associated consumer knowledge and illustrates its importance. Ensuring the correct type of chargers, taking into account driver dwell-time, are installed in the most appropriate locations will be an important factor in maintaining deployment rates and ensuring early adoption is not the preserve of those with home charging. Private developers of charging infrastructure are likely to seek sites offering the best returns, already evidenced by the preponderance of installations in the south-east of the UK [241]. Policies that support charger installations in less affluent areas and remote locations with lower utilisation should be implemented.

The switch to EVs will lead to a substantial reduction in fuel tax revenues [141]; policies to replace that lost revenue must not adversely affect the adoption of EVs. Discussion has already started on road-pricing options, and here there is a link to providing better public transport through the hub concept. Rural commuters could travel fewer miles and participate in daytime smart charging, or potentially V2G. The hub would also work well in conjunction with congestion charging, which could be considered an alternative mechanism for replacing at least some of current fuel duties.

10.1.2 Minimising grid costs and maximising benefits

The work presented here supports existing literature in regard to the impact of EVs on distribution networks. However, the breakdown into geographically centred social groups does reveal substantial variation and highlights the challenges posed in rural locations. It has also shown that a heuristic in-car algorithm can alleviate the majority of high demand periods. Such an algorithm might also be implemented in a smart charger, although to do so would require the charger to have knowledge of the car's range and expected departure time to ensure that driver requirements can be met.

Taking a step beyond local network demand management to consider how EVs may play a role in managing generation intermittency, the analysis raises several key points:

1. Adding 'real-world' EV energy use patterns to future demand forecasts has a significant impact on the optimal mix of solar and wind generation, favouring greater use of solar. However, this effect is likely to be counterbalanced by heat electrification with very high winter demands.

2. Smart charging alone can reduce unserved energy to domestic loads (excluding heating) by up to 40% in a 50% mix of solar and wind.

3. Adding full V2G capability can reduce unserved energy in the same scenario by 66%.

4. Providing nationally focused, renewables balancing services, does not necessarily result in excessive local demands

These, impacts, whilst taking into account consumer travel needs and attitudes to range, are based on 100% adoption and thus unachievable in practice. They also include additional, limited, access to smart charging by those without home chargers; both when at home and at other destinations (accessible to all). Without that access, the benefits of V2G are reduced to ca. 20% reduction in unserved energy.

Perhaps surprisingly, the ADMD's experienced during renewables balancing activity at a national generation level remain acceptable at about 1.5kW in rural settings and under 1kW elsewhere. This is largely a result of cars being charged more widely during the day, which is also consistent with a larger proportion of solar generation.

Having access to EV batteries for either smart charging or full V2G (or indeed V2H) provides a potentially low cost, large scale, medium duration storage resource. It has the capacity and potential availability to avoid investment in other storage systems or reduce total installed capacity of renewables. Management of charging also provides the potential to avoid network reinforcement costs. Delivering this capacity to the market is complex, with many players in the chain and sophisticated communication needs that must simultaneously meet the requirements of drivers, local network operators and national energy balancing. Smart charging also requires communication between the car and the charger or wider control system and a user-friendly driver interface to ensure that adequate range is always achieved. Expanding V2G services economically to all requires the participation of vehicle manufacturers in the development of on-board bi-directional charging capability, which is already beginning to emerge. It seems unlikely that all of these needs will be met without policy and/or regulatory guidance. Currently the frameworks and industry codes available do not adequately address all of these issues and there is a risk that unsuitable charging equipment and incompatible vehicle designs become widespread in the market. Past experience with systems that can have national operational consequences (such as the Accelerated Loss of Mains Change Programme [80]) suggest that core functionality and protection systems ought to reside within equipment over which there is national control of standards and where retrospective modifications can be made to all units should the environment evolve in an unexpected direction. Thus it would appear sensible to deliver smart charging and V2G services through charge points rather than vehicles and vital to ensure that future standards adequately specify the required communication between the two; as a minimum that would include the energy to be added and time by which it must be added, but might also include the maximum energy that can be withdrawn from the vehicle battery.

10.1.3 Delivering equity in charging

The results presented here show that without controlled charging, there will be a need for network reinforcement in some areas with consequential costs. Whilst current cost recovery mechanisms will result in higher charges to BEV owners through greater consumption, peak demand is the key driver of reinforcement costs and those costs are not fully recovered through unit charges. Lower income groups present as slightly later adopters of BEVs, due to the scarcity of used vehicles at appropriate price points and, to some extent, the lack of home charging. There are also fewer car owners amongst those groups. Current charging methodologies will therefore distribute the cost recovery of reinforcement somewhat unfairly with non-car drivers and later EV adopters picking up costs driven by higher income earlier adopters.

Lower income groups, with their reduced access to home charging, are also less able to benefit from the full range of EV tariffs or participate in smart charging or V2G services. Providing more public charging facilities, particularly street chargers and work-time chargers (be those at workplaces, city centre car parks or commuter hubs), that are able to provide smart charging services, ideally linked to users home energy accounts, would both help alleviate this inequality and provide greater resources to manage intermittent renewables and grid constraints.

To deliver benefits outlined requires a substantial investment in public chargers; some 715,000 street chargers for home-based charging and perhaps as many as 8.5 million chargers available at work places and other long dwell-time destinations. Persuading drivers to take the time to plug in when they do not immediately need to charge will be challenging and, as such, the development and deployment of wireless charging may prove essential to maximise the time EVs are connected.

To deliver the described benefits and help alleviate inequities, the following are considered essential:

- Local network demand-based ToU charging.
- Wholesale pricing visibility at low-voltage consumers.
- Access to smart charging for all EV owners.
- Development and adoption of the necessary standards to permit V2G and similar services over standard type-2 and wireless connections. This must include protocols to to read vehicle's stored energy or estimated range.
- 'Open access' public chargers that enable smart assignment of charging costs and benefits through virtual MPAN assignment, or equivalent.
- Adoption of wireless charging by vehicle manufacturers and development of low cost public wireless charging infrastructure.

10.1.4 Integrating public transport in the EV transition

The commuter hub PnR concept presented here is not new, but its integration with the EV transition and on-site renewables has not previously been explored. The case-study analysis shows that a hub can be made almost completely self-sufficient in energy and that electric-bus options could deliver similar NPVs to current diesel technology with a modest carbon tax of 2.00£ t^{-1}.

Assuming that the low operating cost of EVs leads to greater mileage and thus congestion [141], hubs such as this may have a vital role in combination with city congestion charging to facilitate free-flowing urban streets and reduced particulate pollution from road and tyre wear. It would appear expedient to ensure that funds received from congestion charging are directed at solutions such as this that can provide a viable alternative to car use in cities.

The modelling also shows that hubs can enable those without home chargers to fill their batteries at half the cost of existing public chargers. Whilst this cost is still substantially higher than home-charging tariffs, the simulation does not consider how future wholesale prices may vary with national renewable generation output. It is possible that the value of exported power at times of high generation will be sufficiently low to enable on-site EV charging at rates close to those available to home-chargers.

10.2 The BEVI model: limitations and further work

10.2.1 BEVI model limitations

The major limitation in the current work is the lack of data to effectively parameterise the behavioural model. This means that, whilst it has been possible to source some relevant data and base other parameters on empirical observations and to validate the simulation against historical fleet composition, there remains uncertainty about the accuracy of its future forecasting capability. A further, related, limitation is the uncertainty around the transition to MaaS; should this become a significant element of future personal travel, then the total number of vehicles may be substantially lower and with greater utilisation, meaning there will be less availability for flexible charging and discharging.

The simulation of V2G presented simply assumes maximum adoption; this adds to the existing literature in that there is greater detail in regards to what capacity is available where and includes aspects of human behaviour in regard to range desires. However, there is no attempt in the current model to simulate the adoption of V2G contracts (or indeed any other form of charging). This would be a desirable feature, but requires greater understanding of driver attitudes to operating cost, bearing in mind costs compared to ICE vehicles are already much reduced, and relinquishing control to a third party.

A further limitation of the model is the time taken to complete a simulation with an adequate number of agents. In the final incarnation, a single run with 1,000 households and 1,540 car owners runs at approximately 7 minutes per year forecast, with a typical simulation being over 35 years and taking approximately 4 hours. This was after reducing the volumes of data being stored by the simulation; with full data storage, run times were up to 12 hours. Whilst this is acceptable, it limits the ability to run the sensitivity analyses or optimisations within a reasonable time frame.

10.2.2 BEVI model further work

A first stage in future work would be to design a survey that enables complete parameterisation of the current model and detailed validation of its performance against the very recent increases in sales of BEVs where, by mid 2021, BEV sales were up 54.4% on the same period in 2020 [200]. Such a survey ought to elicit further data on the potential for MaaS, specifically the types of consumer and nature of journeys that might be undertaken. This would allow adjustment to the driver population and journey types to explore the impact of MaaS on adoption, energy demands and availability for grid services. This work would also enable meaningful addition of tariff and charging contract adoption and simulation of future demands and V2G availability based on consumer choices.

It is primarily the behavioural component of the model, with its need for substantial inter-agent communications and multiple array calculations to assess and compare car models during selection, that drives the model execution time. A detailed survey might reveal elements of the existing model are over-specified, for example the breaking down of operating costs to taxes, fuel and maintenance. It seems likely that the model could be optimised further to reduce run times and/or allow modelling with a larger number of agents, which may smooth some of the volatility seen in those socioeconomic groups with lower populations.

A further model refinement would be to add ambient temperature adjustment to the BEV performance, matched to the timing of the generation data. This would also require careful examination of the NTS data sets to explore how best to adjust the travel undertaken to reflect seasonal differences. This activity is potentially quite important in respect of the V2G modelling due to the significant seasonal variation in wind and solar generation and variability in monthly distances travelled by drivers. Ideally these NTS profiles would also be matched to more refined household load profile data reflecting use patterns in different socioeconomic groups.

With these model refinements in place, it would be practical to explore alternative algorithms for smart charging and V2G and to explore V2H (and vehicle-to-business) type contracts.

In the present model, the number of cycles completed by each BEV battery is counted and used in a simplified degradation model. Some initial analysis of mean cycles under different scenarios suggests that V2G may not add substantially to the total cycle count, which is probably the result of driver range preferences limiting discharge per vehicle. Scenarios where only part of the car owner population adopt V2G do show an increase in mean cycles, thus further work to understand the extent of V2G adoption would be valuable in determining the degree of cycling and hence the cost of V2G to vehicle owners.

From a policy perspective, it is evident that as the number of fossil fuelled vehicles decline, so will associated tax revenues. Fuel duties alone (excluding VAT on receipts) raised £28Billion in 2019-20, some 3.3% of all tax revenues [169]. Since the model developed here makes use of detailed journey records and determines energy usage, it would be an ideal platform to explore future policy options, such as a mileage related tax, and to understand their impacts on different social groups and geographies.

10.3 The REVIT model: limitations and further work

10.3.1 REVIT model limitations

The REVIT model's major limitation is in the estimation of vehicle efficiency. The simulation currently assumes that efficiency varies only with ambient temperature, with no route adjustment factors due to the lack of reliable data. The number of passengers on the vehicle is also likely to impact on efficiency, largely through changes in air-conditioning demand rather than weight. The battery degradation model is highly simplified, using only cycle information, a more sophisticated degradation model would be useful in further testing scheduler optimisation. The options for charging of buses during route operation are also limited in the simulation.

The simulation currently creates the minimum number of buses required to complete the timetable over a specified 'contract' lifetime and determines an estimated NPV taking into account the residual values of any equipment left at the end of the contract. In practice, any such operator contract would also require spare vehicles to account for maintenance and breakdowns; this is not currently included and may affect the relative merits of the options presented.

The hub battery operating algorithm only seeks to optimise the use of on-site generation and low overnight tariffs for bus energy consumption and does not consider how the capacity might be used to support hub car charging. Furthermore, future energy scenarios, where prices are driven by the availability of excess renewable generation or otherwise, imply that low hub generation will be coincident with high import costs, increasing the value of onsite storage.

10.3.2 REVIT model further work

Improving the efficiency modelling would provide greater confidence in the results. To reduce processing overhead, this might best be done in a separate simulation that seeks to determine terrain, bus passenger loading and ambient temperature adjustment factors to be applied to a base efficiency for each route leg. The existing REVIT model would then be modified to include those factors.

Extending the use of opportunity charging to intermediate stops would be useful addition to explore its impact on the number of buses required under the electric scenarios. In combination with a more sophisticated battery degradation model incorporating rain flow analysis, such as that introduced by Muenzal et al. [155], this would allow the exploration of alternative bus selection algorithms to minimise capital investment in electric buses and battery replacements.

Allowing the ability to specify a minimum number, or percentage, of spare vehicles would also improve the accuracy of the NPV comparisons between hydrogen, electric and mixed solutions. This may reveal that electric solutions perform better than shown, due to their lower capital cost, or that mixed solutions offer greater benefits, particularly where a mixture of route lengths and terrains are involved.

Expanding the hub battery algorithm to include managing the cost of energy for car charging might further reduce charging costs, although this is only likely to be the case where a more sophisticated tariff structure, incorporating 'real-time' adjustments for the volume of renewable generation, is included. This is because the modelling shows that battery costs are currently too high to make arbitrage at existing price differentials a viable application. It may also be appropriate to consider the hub as a location for smart charging and V2G such that the cars themselves could provide the storage resource to support greater self sufficiency and manage the cost of charging for other vehicles. Currently the simulation only considers EV drivers charging during the daytime. However, a suitably located hub which city-based EV owners can access for overnight charging, using buses to return home to their city-centre dwellings, might also prove viable. Whilst this could be modelled readily in the existing REVIT model, justifying this as a plausible consumer charging strategy would need further research and survey work.

Acronyms

ABM agent-based model. 6, 8, 16–20, 22, 29, 43, 46

ACEA European Automobile Manufacturers Association. 26

ADMD After Diversity Maximum Demand. 195, 197, 219, 220

AFV Alternative Fuelled Vehicles (including hydrogen, synthetic fuels and electric variants). 14, 16, 17, 23, 28, 32, 43, 50, 110–113

BEV battery electric vehicle. 1, 5, 11, 15, 16, 18, 19, 23, 26, 28, 30–32, 45, 49, 51, 53, 68, 85, 86, 91, 93, 95, 98, 101, 104–109, 113, 114, 116, 117, 163–169, 173–179, 181–189, 191–193, 195, 198, 199, 202, 203, 207, 208, 211, 213, 214, 218, 220, 222, 224, 230, 253, 256

BEVI 'Behaviour-based Electric Vehicle adoption and grid Integration'. 6, 7, 43, 136, 162, 191, 245, 249

BIK Benefit-in-Kind. 48, 49, 88, 167, 174–176, 181, 182

BMS Battery Management System. 95

DNO Distribution Network Operator. 197

EHS English Housing Survey. 63

EV Electric Vehicle. ii, ix, x, 1–18, 20–26, 28–35, 37, 38, 41, 42, 45, 50, 51, 53, 56, 68, 72, 73, 86, 88, 92, 95–104, 106, 107, 113, 116, 119–121, 124, 136–138, 162–165, 172–176, 181, 188, 191–194, 200, 202–205, 207, 211, 212, 215, 222, 224–229, 247–255, 258

EWMA Exponentially Weighted Moving Average. 77, 211–213

HEV Hybrid Electric Vehicle. 19, 28, 45, 106, 111, 113, 114, 189

ICE Internal Combustion Engine. ii, 11, 19, 23, 26, 28, 32, 45, 50, 51, 54, 55, 68, 72, 85, 86, 88, 89, 93, 98, 99, 106–109, 113, 114, 116–118, 163–165, 167, 168, 173–176, 178, 179, 181, 182, 184, 186, 189, 192, 203, 250, 251, 255

kWp kilowatts peak installed capacity. 153, 157, 231, 238, 239

MaaS Mobility as a Service. 5, 24, 163, 255, 256

MWp Megawatts peak installed capacity. 232–237

NGC National Grid Company. 24–26, 117–119, 163, 164, 189, 190

NPV Net Present Value. 121, 123, 147, 237–239, 241, 245–247, 257, 258

NREL National Renewable Energy Laboratory (US). 33, 158

NTS National Travel Survey [223]. 55, 59, 61, 63, 65–67, 70, 86, 88, 89, 101, 103–105, 171, 172, 195, 196, 256

ONS UK Office for National Statistics. 61, 62, 64, 65, 171

PEM Polymer Electrolyte Membrane. 142

PHV Plug-in Hybrid Electric Vehicle. 19–23, 26, 28, 32, 45, 49, 50, 85, 88, 95, 104, 106, 113, 114, 181, 183, 189

PLC Power Line Communications. 225

PnR Park and Ride. 36–39, 41, 120, 148, 233, 254

REVIT 'Renewables and Electric Vehicle Public Transport Integration'. 6, 7, 120, 122, 231, 249, 250, 257, 258

SoC State of Charge. 35, 73, 74, 86, 88, 94, 95, 97, 100, 101, 128, 131, 134, 138, 158, 214–216, 218–221, 225, 246

SoH State of Health. 40, 95, 96, 127, 135, 154, 240

STECCAR 'Simulating the Transition to Electric Cars using the Consumat Agent Rationale'. 22, 23

TCO Total Cost of Ownership, including depreciation. 20–22, 28, 29, 40, 50, 84, 97, 166, 168, 186, 187

ToU Time-of-Use. 48, 67, 98, 184, 194, 195, 200, 202, 224, 229, 254

V2G Vehicle-to-Grid. 1–4, 6, 7, 9, 11, 14, 21, 29, 31–35, 41, 207, 208, 211–215, 217–223, 225–227, 229, 230, 249, 251–258

V2H Vehicle-to-Home. 207, 211, 219, 220, 225, 252, 256

VAT Value Added Tax. 47, 181, 189, 257

VED UK Vehicle Excise Duty. 49, 168, 169, 175–177, 181, 182

WLTP Worldwide Harmonised Light Vehicle Test Procedure. 51, 53, 127, 133, 134, 192, 193

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