Evaluating the role of behavior and social class in electric vehicle adoption and charging demands
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SUMMARY

Understanding electric vehicle (EV) adoption rates and charging patterns is critical in enabling grid operators to maintain quality of supply and offers the potential to procure network services and avoid or postpone capital investments. Agent-based models have separately been shown to be useful in modeling EV adoption, policy options, behavioral influences, and grid impacts. In this work, we bring together these threads with real world travel data to present a multi-scale, behaviour-based EV adoption and use model able to replicate historical changes in vehicle fleets and match the most recent real world EV charging profile data. We have shown how our model can be used to simulate the impact of policies and consumer behavior on the rate of EV adoption across socio-economic groups and the locational grid impacts of EV charging, and as such we believe it to be of value to policy makers, grid operators, and demand response aggregators.

INTRODUCTION

Governments around the world are seeking to reduce emissions from the transport sector in line with national and international commitments. The deployment of plug-in electric vehicles (EVs) has the potential to reduce carbon emissions and also to improve local air quality through reduced particulate and NOx amongst others (Department for Business Energy and Industrial Strategy, 2017; Hampshire et al., 2018). The EU has imposed manufacturer fleet-based average emissions limits reducing to 95 g CO2/km by 2021 (European Commission, 2017), a target requiring some degree of electrification. In China, the government’s ‘New Energy Vehicle Mandate’, similar to that employed in California, provides a strong incentive for manufacturers to develop electrified models; China is currently the largest EV market globally with some 47% of all EVs on the road (International Energy Agency, 2020). As of March 2020, 16 countries (12 European) had taken various actions to phase out Internal Combustion Engine (ICE) cars (Burch and Gilchrist, 2018). The UK Government, for example, proposed a target of 2040 for a ban on the sale of pure ICE cars in 2018 (Burch and Gilchrist, 2018), but in 2020 announced plans to bring this forward to 2030. Despite these proposals, there are few studies that seek to forecast individual country EV adoption and those that do tend to pre-date the introduction of EV models by many car manufacturers, which provide vehicles at lower cost points across a wider range of market segments. In the case of the UK, the only recent work in this area appears to be that of National Grid ESO (NGC), the electricity system operator, where various forecast cases are provided in the Future Energy Scenarios report (National Grid ESO, 2020).

EVs are substantially more efficient from battery to wheel than the equivalent tank-to-wheel efficiency of ICE vehicles and thus the electricity required for charging is likely to be some 30% of the petrol/diesel needs of the current fleet (Hass et al., 2014). While spare generation capacity exists in most grid systems, unmanaged charging of EVs could be problematic. Conversely, managed charging could assist grid operators to avoid wind and solar curtailment at times of high generation, a policy that would enhance the environmental credentials of EVs. Within local distribution systems EVs could also be problematic, with the potential to significantly increase local demands, overload cables and transformers within low voltage systems (Papadopoulos et al., 2012; Richardson et al., 2013). Within the UK, the typical power rating of residential EV chargers is 7.2kW compared to a design After Diversity Maximum Demand (ADMD) of 1.5kW for typical households. A UK joint industry and academia project, ‘Customer-Led Network Revolution’ (Barteczko-Hibbert, 2015), including a small sample of EV drivers, showed that ADMD can vary between

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different social groups and explored the impacts that EVs and heat pumps might have. This work notes that the number of customers on the circuit has a significant impact on the extent to which demand is smoothed, but suggests an ADMD of around 2kW with 100 customers.

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 (Papadopoulos et al., 2012) through averaging of travel survey data (Ihekwaba et al., 2017) to the use of agent based models (ABMs) generating their own probabilistic travel patterns based on survey data (Torres et al., 2015; Olivella-Rosell et al., 2015). ABMs are a class of simulation which attempt to model individual consumer behavior and aggregate this to reveal emergent behavior across a population. However, charging studies to date have not taken into account the socio-economic status of locales within the network, identified as relevant in the ‘Customer-Led Network Revolution’ project (Barteczko-Hibbert, 2015), and have not implemented EV adoption models to any great extent, relying instead on assuming various levels of penetration.

Shafiei et al. (Shafiei et al., 2012) developed an Alternative-Fuel Vehicle (AFV) growth ABM using consumer choice input data to parameterize their agent decision algorithm. While this model incorporates elements of peer communication and range anxiety, it assumes that purchasers are able to undertake total cost of ownership (TCO) calculations and that this forms a key element of the purchase decision. In practice, studies by Axsen et al. (Axsen et al., 2013) and Schuitema et al. (Schuitema et al., 2013) show that social influence, hedonic and symbolic vehicle attributes play a significant influencing role in car purchase choices. Eppstein et al. (Eppstein et al., 2011) add further social influence in their ABM, which focuses on plug-in hybrid vehicles (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 while 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 range anxiety and need for charging infrastructure. Krupa et al. (Krupa et al., 2014) 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, while 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 drivers of larger cars generally unwilling to trade down where PHVs were not available in the same segment as their existing vehicle.

A 2016 study by Adepetu, Keshav and Arya (Adepetu et al., 2016) focused on San Francisco; their consumer agents include a ‘greenness’ variable to represent a person’s tendency to incorporate lower carbon footprint into their purchase decision. Their model also incorporates a function representing the ability of individual agents to accurately estimate TCO of a vehicle and thus the relative benefits of lower running costs for EVs vs. lower initial capital cost for conventionally fueled vehicles. The study employs temporal and spatial information based on National Renewable Energy Laboratory survey data of 366 San Francisco residents covering work day and non-work day driving patterns, with simulated routes within the city. This enables 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. However, the adoption element of the model includes only private vehicle ‘cash’ purchases whereas some 59% of new car purchases are made by fleet buyers in the UK (DVLA, 2019); only two models of EV are included and no long-distance trips are simulated, thus, users do not experience range anxiety. Ahkamiraad and Wang (Ahkamiraad and Wang, 2018) have presented an agent-based EV adoption model that aims to simulate adoption at zip-code level in New York. Each zip-code is an agent with differing adoption rates based on its population characteristics and communication also occurs between neighboring areas. An adoption and annual energy consumption spatial model is developed, but this does not resolve to half-hourly demand data, which is essential in planning network capacities.
The ‘Consumat’ model, which was first put forward by Jager, Jannssen and Vick (Jager et al., 1999) in 1999, brought together various theories relevant to understanding consumer behavior in a methodology applicable to ABM. A Consumat is an agent within an ABM that participates in four processes: deliberation, social comparison, imitation, and repetition of previous actions. The Consumat model was further updated by Jager and Jannsen in 2012 (Jager and Janssen, 2012), this introduced variability in the capability of agents to, for example, assess the utility of a purchase decision.

Kangur et al. (Kangur, 2014; Kangur et al., 2017) have developed an agent-based simulation for diffusion of EVs known as STECCAR (Simulating the Transition to Electric Cars using the Consumat Agent Rationale) based on a Consumat model. Consumats here 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 optimize 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. The evaluation of needs and mental state results in four different agent conditions as illustrated in Figure 1.

The STECCAR model evaluates purchases of the three main car groups (Internal Combustion Engine (ICE), PHV, and BEV) 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. This model does not however take into account brand or segment loyalty and does not attempt to project AFV uptake onto electricity network demands.

Numerous studies have shown the effects of brand loyalty on purchasing decisions and May (May, 1971) showed the degree of brand loyalty in relation to Californian car purchasing is also related to social status while Danish et al. (Danish et al., 2018) showed how a number of aspects of brand are correlated with purchasing decisions. Although there are no recent UK academic studies specifically looking at brand loyalty and car purchase choices, a 2017 industry survey by AutoTrader (AutoTrader/AM-Online, 2017) suggests...

Figure 1. Illustration of Consumat states based on work by Kangur et al. (Kangur, 2014)

The clouds show likely alignment with Roger’s diffusion of innovation model (Rogers, 2003), however, this may not be strictly true since deliberators, for example, may have a set of preferences that deliver greater satisfaction by retaining an ICE vehicle.
around 25% of volume-brand purchasers repeat buy but that fell to 16% for premium brands. The same survey showed that buyers exhibit even greater body-type (segment) loyalty, with an average of 41% repeat purchasing. The survey also noted an increase in SUV and 4x4 repeat purchasing but a reduction in super-mini repeat purchasing; this may thus, in part, reflect a general desire to purchase higher status (typically more expensive) vehicles. These levels of brand and segment loyalty are significant given that EVs, in the early years of deployment, have not been available across all segments and brands.

In this study, we bring together these different strands to develop an ABM, the Behaviour-based Electric Vehicle Grid Integration (BEVI) model that is able to simulate the uptake of AFVs, including HEVs (non-plug-in hybrid-electric), PHVs, and BEVs, taking into account social interactions and limited TCO calculation ability. This work extends beyond existing ABM EV modeling by combining a behavioral model, incorporating charging knowledge acquisition, with a representative suite of vehicles and detailed travel diaries to provide a simulation able to both project EV adoption at a societal and social group level together with evolving impacts on the electricity grid on highly granular time and geographic scales. Applying this model to the UK market as an exemplar, we investigate the impacts of brand and segment loyalty and how availability of price parity with ICE vehicles and larger ranges impact on diffusion rate. We show that such a model can be effectively used to forecast the impact of AFV uptake on electricity demands both nationally and critically at a local distribution level taking into account socio-economic factors.

The methodology behind the BEVI model, and the datasets employed are described in the STAR Methods section. In the Results and Discussion section, we first analyse the performance of the model and subsequently explore the impacts of tax policy, brand loyalty, range, and pricing. We also validate the charging demand against recent real-world data and show how the model can be used to forecast demands in different locations. We finish with general conclusions, areas for further work and a review of the study limitations.

RESULTS AND DISCUSSION

We present here a regional analysis covering an area of Northern England that encompasses urban conurbations, rural locations, and small and medium-sized towns, and which includes a broad cross section of socio-economic groups. We demonstrate how these factors impact on adoption rates and charging demands on local grids.

ABMs have many complex interactions which can render them opaque to understanding by those unfamiliar with their development. As such, providing confidence that the model is verified and validated before application to real world problems is critical (Rand and Rust, 2011). In this section, we first present verification that the underlying functionality delivers the expected results by comparing ICE and BEV buyers against a number of parameters where differences would be expected and identify features of interest. We also validate the model against historic purchase choices in the UK market and explore how brand loyalty can improve model accuracy. We further validate the simulated system demand profiles against recently gathered real-world data and, finally, apply the model to the problem of establishing demands imposed by EVs on specific types of network and consumer; hard-pressed, metropolitan, suburban, and rural. We discuss the implications of these demand patterns on network utilization and equitableness of cost recovery.

All the results presented here are based on simulations with 1000 homes, corresponding to some 1524 car owners. This number was chosen as a practical compromise in regard to computation time. Although not illustrated here, model results are similar once more than 500 households are included, provided that peer connections result in a highly connected network. This is indicated by a Grannis Factor (Grannis, 2010) greater than 1; in our simulation the Grannis factor is 1.2. The mean number of peer connections between agents was 9.01 with a minimum of zero connections and maximum of 50.

Preferences reflected in purchase decisions

Here, we set out a selection of results demonstrating that the simulation approach is able to reflect constraints on car buyers and their preferences. For this purpose, we focus on the period for 25 years post-2012 (when BEVs first enter the UK market) and compare sales 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.

Figure 2A illustrates the mean greenness index of ICE buyers and BEV buyers from the introduction of BEVS in 2012–2038. This indicates that car owners with a high greenness index are more likely to be EV purchasers, but over time, the greenness of first-time BEV buyers decreases as BEVs become more commonplace. The oscillations in early years also show an interesting aspect. In our model, the greenness and performance weightings of drivers are loosely inversely correlated and examination of the data shows that early EV adopters with low greenness weights tend to be those with high performance weights, indicating an attraction to the impressive acceleration times available for EVs. The greenness of the buyer is however a significant influencer for early adopters suggesting that measures to increase the average level of

![Figure 2A](image)

**Figure 2. Constraints and preferences of buyers impact on likelihood of BEV purchase**

We plot here the mean of the car-owner’s value of each characteristic over time for pure ICE and BEV purchasers.

(A) Impact of Buyer ‘Greenness’ on Purchase Choice. The dotted line indicates the greenness of first-time BEV buyers showing slight decline in greenness over time.

(B) Impact of household income, showing that early BEV adopters typically have higher income.

(C) Mean charging knowledge (index), showing BEV buyers have a greater knowledge of charging environment.

(D) 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.
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.

Figure 2B presents the mean monthly household income of BEV owning and ICE owning households over the modeled period. Here we see that 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, is likely to be beneficial until price parity is reached.

In Figure 2C we illustrate 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 2D compares the minimum and preferred (target) range for BEV and ICE buyers illustrating that while 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 modeling 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. While 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, particularly 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 (RAC, 2019), which also suggests greater emphasis on safe driving periods (2–3 hr continuous driving) and more attractive locations to break journeys for charging would contribute usefully to reducing desired vehicle ranges.

**Accurate hindcast of fuel modal shift**

With very little data on which to assess the accuracy of the model for large scale changes in drive train, we instead compare the historic mix of petrol and diesel vehicles in the UK fleet. Figure 3A shows that the model can accurately reflect the shift from petrol to diesel during the 2000’s. We have not attempted to model the ‘Diesel-Gate’ scandal (BBC, 2015), which led to a rapid slowdown in the sale of diesel cars from 2015, but we do include changes to fuel-based tax regimes. From 2017, the model error for petrol vehicles increases and this can be traced to an overestimate of the shift to AFVs.

**Brand and segment loyalty reduces AFV uptake rates**

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, we simulate brand loyalty by including a probability that any given car within the car owner agent’s purchase pool is available in a specified brand. Figure 3B illustrates the proportion of vehicle manufacturers offering each of the three types of AFV modeled 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, mid-way between the suggested fossil-fuel car sales ban dates proposed by the UK government. The data points, based on analysis of DVLA statistics (DVLA, 2019), 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 loyalty 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 purchase decision, segment loyalty was modeled 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 or budget constraints) were allowed to move segment, but
those with children were still prohibited from purchasing the smallest class of car. In respect of brand loy-
ality, a car was considered a valid option if:

- the car owner was not brand loyal;
- it was the same model as the owner’s existing car;
- it was a petrol or diesel car (on the basis all manufacturers produce such cars); or
- with a probability given by Figure 3B 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 3B, other brands did not emerge until around 2014. In Figure 3C, we present the modeled HEV adoption curve with and without brand loyalty together with the actual UK market share.
showing that the addition of our 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 3B) and an overestimate of BEV sales.

Figure 3D presents the modeled forecast of EV adoption with and without brand loyalty from 2010 through to 2038. We include also an ‘ICE parity’ comparison curve and forecast PHV market share. We can see here 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 542 km 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 480 km at a launch cost of £35,000. The effect of this (Figure 3D) is that the adoption of PHVs, with a range similar to ICE vehicles, continues to accelerate while 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, we can see that brand loyalty can be a significant factor in adoption. Figure 3D (inset) also shows that the model over-estimates the adoption of BEVs in early years. It is, however, reasonably accurate for both HEVs and PHVs. We speculate that this is the result of additional Status Quo bias (Latheef et al., 2018; Cao et al., 2011) since BEVs represent a bigger step away from conventional ICE than to HEVs or PHVs. In the ‘ICE Parity’ 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 347 km (for a mini) to 825 km for the best performing vehicle. The modeling suggests that there is, or will be by 2025, latent demand for longer range, lower cost EVs. Thus, if market predictions of price parity in 2025 are correct (Bloomberg, 2018), and if this is accompanied by an increase in range, then a rapid acceleration in EV adoption is likely.

Vehicle purchasing strategies and policy influences

Figure 4A sets out the ownership models, without ICE parity, over the 20-year period (the maximum modeled car lifetime) from 2013 to 2033 when the curve has flattened. In this figure, all new company and personal leases are new cars, while loans and purchases can be new or used. We see here that company leases of BEVs begin from 2020 when the tax benefits are substantially improved, demonstrating the importance of tax policy in the UK market where fleet vehicles represent ca. 59% of new vehicle purchases. Commencing from 2023, we begin to see greater direct purchases of BEVs, reflecting the availability of depreciated fleet cars arriving in the market. Tax benefits on fleet BEVs assist in two ways: First, they provide
a lower cost entry point for BEV buyers and, second, car owners are more likely to have communication with a BEV owner, thus allowing adoption of BEVs by more imitators in the simulation.

The impact of ICE vehicle sales bans on adoption

In this section, we show the impact of the proposed UK policy for ICE vehicle sales bans, initially proposed for 2040, but recently brought forward to 2030. In order to better reflect the availability of new EVs, these simulations include car-maker agent functionality to generate new models based on the range concerns of drivers. New models of EV are created from 2020 onward with an additional 50km capability when 1% or more of car owners reject an EV model due to insufficient range. The battery sizes and costs of the new vehicles are adjusted based on Bloomberg battery and glider price forecasts (Bloomberg, 2018) and expected efficiency reduction with higher battery mass; full details are provided in STAR Methods.

Figure 4B compares the revised model results with the four scenarios used in the NGC 2020 Future Energy Scenarios document (National Grid ESO, 2020). Note that to express these figures as percentages, the total number of cars takes into account NGC’s forecast of Mobility as a Service and its impact on total vehicle numbers.

We can see from this analysis that the model-generated cars (‘Market EVs’), i.e., a more realistic expectation of the evolution of cost and range forward to 2030, do not quite match the BEV-ICE parity case (Figure 3D), but are significantly better than assuming only existing BEVs are available. We can see here that a ban in 2040 has little 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 modeling does not include any additional media coverage generated as a result of the ban being introduced; it is possible that this would accelerate uptake prior to 2030 resulting in a smoother adoption curve, perhaps more closely aligned to the NGC ‘Consumer Transformation’ case.

NGC include an estimate of Mobility as a Service (MaaS) adoption for the different scenarios; we have presented the adoption curves here as a fraction of expected number of vehicles as that changes over time under the NGC scenarios. NGC’s ‘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.

Electricity demand forecasting

In this section, we demonstrate that the model is able to generate realistic electricity demand profiles. Figure 5A compares the modeled household charging profiles (with half hourly profile averaged to hourly) in

Figure 5. Electricity demand forecasting and socioeconomic/locale groupings

(A) Comparison of modeled 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 (National Grid, 2019). (Two outlying data points from 2019 data removed for clarity - caused due to small number of cars.)

(B) Location plot of social/locale groupings (high density area, center right is Sheffield, area top left is Huddersfield/Dewsbury) and adoption of EVs by the same groupings assuming only current EV models. Bracketed figures show percentage of households each group represents.
2019 and 2035 to real world averages from a 2019 National Grid Company (NGC) sponsored project which collected data on 8 million charging events (National Grid, 2019). Only home charging events are included in this analysis. 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, we have assumed an immediate ‘charge on return home’ strategy 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 charging produces a flatter profile. We have included a 2035 profile here to illustrate the situation with more cars and therefore more smoothing, which delivers a better fit to the NGC data. Spikes in the modeled data can be caused by returns from unplanned trips.

In Figure 5B we show how uptake (based on current EV models) varies with Office for National Statistics (ONS) UK Government: Office for National Statistics (2018) classification and how these map to locales over the area simulated (the map also shows how agents are linked in the simulation). By 2035, only 11% of ‘Hard Pressed’ car-owning households own EVs compared to some 25% and 23% of ‘Rural Residents’ and ‘Suburbanites’ respectively. Examination of the underlying data shows that all ‘Hard Pressed’ buyers until 2023 actually have high household incomes compared to average. This can occur in the model because social groups are associated with postcode areas, not actual incomes; thus, a high income household can occasionally occur in a predominantly low-income area. This distribution of EV ownership, while not unexpected, raises the prospect that the lower operating cost of EVs compared to ICE vehicles will not be available to the lowest income sections of society for some time.

Figure 6 presents the diversified weekday residential charging rate during each half-hour market trading interval during a sample February Wednesday as penetration of EVs progresses from 2014 through to 2038 for four different car-owning social groups that also correspond to geographic locales to a large extent. We have used the ‘EV Parity’ model, which results in much higher adoption rates in order to more clearly identify future trends; the percentage adoption of EVs (by existing car owners) is shown on the right hand scale. The figures illustrate features pertinent to uptake in different areas and differences in charging patterns. These plots show occasional peaks that appear out of character with the general trend; this can occur due to multiple unplanned journeys ending at the same time. It is worth considering that such peaks may occur in the real world, particularly at key times such as the end of a public holiday, when many families might return from trips at similar times.

The ‘Hard Pressed’ group (Figure 6A) are mainly, but not exclusively, located around city centers (see also STAR Methods, Figure S9). The adoption rate lags our other city-centre group, Multicultural Mets (Figure 6B) and residential charging is much lower due to fewer households having access to home charging and fewer miles being driven. Where it does occur, home charging falls mainly around 8pm, while Multicultural Mets peak later at around 10pm. We see here the effects of reduced commuting compared to suburban and rural residents and more evening activities compared to our Hard Pressed group. It appears clear from this analysis that the more wealthy in society will drive the need for grid reinforcement where residential charging is concerned. The distribution of charging during the day also indicates that it will typically fall outside of normal city peak periods and, therefore, greater utilization of existing assets may be possible.

Moving out from the city center to suburban households, in Figure 6C we see charging demands spread over a longer period between 14.00 and 21.00, resulting in lower peak demands than might otherwise occur. Here, we also perhaps begin to see ‘school run’ effects; a higher density of charging events around 15.30 to 16.30. In rural communities, Figure 6D), the peak is clearly defined around 19.30, perhaps reflecting longer commutes which result in both a later return home and more overlapping of charging events. These relative high peaks in rural locations, where grids may be weaker, suggest greater need for charge management solutions, or perhaps more use of daytime charging at city-based work or shopping locations.

Comparing these different locales, we can envisage that the timing and types of investment needed to manage EV charging demands will vary. Rural locations with potentially weaker grids may require charge management solutions sooner than city center locations, which, given the apparently more time-distributed nature of charging, may be able to make use of spare capacity in assets designed for daytime and early evening commercial peak demands. Our analysis amplifies the expectation that more wealthy locales are likely to lead adoption of EVs and will also require earlier and more substantial investment to manage peak
Demand. Ideally, this would be paid for by those in receipt of the benefits. As such, more emphasis on demand, rather than energy, charging may be justified. Such a strategy may also encourage more off-peak charging, reducing the need for local reinforcement and lowering system stresses more generally.

Conclusions

The goal of this study was to better understand how policies interact with behavioral factors to influence the uptake of EVs and charging strategies, and ultimately the impacts this will have on grid systems. In this paper, we have shown that a sophisticated ABM combining human behavior modeling and peer interaction with real-world travel data can emulate past behaviors and assist in predicting both the adoption rate of EVs and their impacts on the electricity grid. Further work to refine the parametrization of the model and explore the optimal ranges and costs of future EVs should elucidate the growth curve post 2025.

Understanding how different policies, such as tax incentives, and vehicle range and price-point availability impacts on uptake rates will be important in identifying the necessary timing and scale of network investments or smart controls. BEVI uniquely combines vehicle technical parameters and behavioral responses with detailed geographical information allowing these interventions to be targeted in the most effective locales. By applying this approach to the UK, we have demonstrated that less wealthy members of society will benefit from EVs, specifically their lower running costs, much later, and this raises important social
equity issues, not just around direct mobility costs, but also in the costs to provide for increased maximum demands. The model provides a means to explore how policy can help mitigate this inequality.

In a recent paper exploring the value of seasonal energy storage for the integration of wind and solar power, Guerra et al. (Guerra et al., 2020) note that hydrogen becomes the lowest cost storage medium for durations of over 3.1 days in the 2050 to 2070 period. Our modeling indicates a desire for higher range vehicles of some 50-100kWh battery capacity; however, the average daily use is only in the order of 6-7kWh per vehicle. Taking an average 75kWh battery, this indicates that circa 50kWh per battery could be made available while retaining the ability to complete 3 average days of use. With around 32 million cars (DVLA, 2019) in the UK, this could provide 1.6TWh of storage, equivalent to about 40 hr of average electricity demand (UK Government: Department for Business Energy and Industrial Strategy, 2018a), and thus could contribute significantly to the sub-3.1 day storage requirement. The BEVI model could be applied to analyze practical availability of EV battery capacity and explore policies and incentives to facilitate adoption of the Vehicle-to-Grid contracts necessary to deliver this service to the market.

While this work has focused on the UK environment, the core datasets employed are of a nature provided by many governments and as such the model could be applied to other countries with differing policies, driving patterns, socio-economic groupings, and associated home charging availability. This may identify trends of interest to policy makers, vehicle manufacturers, and network operators.

Limitations of the study
The main limitation of the study as presented is the lack of detailed survey data to parameterize some elements of the behavioral model. While we have shown that key behavioral features have been captured, survey work to refine those parameters generalized in our approach may provide more robust outcomes.

While we have presented here a specific UK location around Sheffield, in practice, the data used is representative of the UK as a whole, with households from socio-economic groups mapped using ONS postcode areas; i.e., the travel datasets are representative of the behaviors of those groups nationally rather than for the specific locations indicated. In this work we chose areas including urban, suburban, and rural locations that include all socio-economic groups broadly in proportion to those found across the country as a whole.

One further limitation of the BEVI model is that it makes no attempt to forecast the shift to MaaS. However, the simulation is adaptable to remove either individuals or journeys most likely to transition to MaaS; a valuable area for future work would be exploring how to integrate the model with MaaS adoption simulations to improve the forecasting capability.

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SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2021.102914.

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AUTHOR CONTRIBUTIONS

Conceptualization, R.L. and S.B.; Methodology, R.L.; Software, R.L.; Investigation, R.L.; Writing - original Draft, R.L.; Writing - Review & Editing, S.B., R.L.; Visualization, R.L.; Supervision, S.B.

DECLARATION OF INTERESTS

Dr. Solomon Brown is a director of the Center for Doctoral Training in Energy Storage and its Applications. There are no other interests to declare.

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## STAR METHODS

### KEY RESOURCES TABLE

| REAGENT or RESOURCE | SOURCE | IDENTIFIER |
|---------------------|--------|------------|
| Deposited data      |        |            |
| Historic UK road fuel prices | UK Government | https://www.gov.uk/government/statistical-data-sets/oil-and-petroleum-products-monthly-statistics |
| Tariff data         | Bulb, UK | http://www.bulb.co.uk |
| EV Charging costs and charge point data | ZapMap | https://www.zap-map.com/ |
| Greenhouse gas conversion factors | UK Government | https://www.gov.uk/government/publications/greenhouse-gas-reporting-conversion-factors-2018 |
| Company car tax rules | UK Government | https://www.gov.uk/government/statistics/company-car-tax-rules-2002-to-2005 |
| EV performance data | EV Database UK | https://ev-database.uk/ |
| General car specification data | Parkers | https://www.parkers.co.uk/car-specs/ |
| Battery pricing     | Bloomberg | https://about.brief.com/electric-vehicle-outlook/ |
| Road length data (charger requirements) | UK Government | https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/722478/road-lengths-in-great-britain-2017.pdf |
| National Travel Survey (detailed travel diaries and driver data) | UK Government | https://www.gov.uk/government/collections/national-travel-survey-statistics |
| Household Incomes   | UK Government, Office for National Statistics | https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/incomeandwealth/bulletins/householddisposableincomeandincomeinequality/yearending2018 |
| English Housing Survey, potential for home charging/off-street parking data | UK Government | https://doi.org/10.1017/CBO9781107415324.004 |
| Expenditure data on motoring | UK Government | https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/expenditure/adhocs/009816householdexpenditureonmotoringforhouseholdowningacarbydisposableincomeanddeciilegroupukfinalyearending2018 |
| Non-stop driving durations | Royal Automobile Club | https://www.rac.co.uk/drive/news/motoring-news/rac-research-reveals-safety-risk-how-long-do-you-drive-without-stopping/ |
| Car reliability and costs | TUV/Autobild | http://www.anusedcar.com/index.php/tuv-report-year-age/2017-6-7/579%0A |
| Real-world battery degradation rates | GeoTab | https://www.geotab.com/blog/ev-battery-health/ |

### RESOURCE AVAILABILITY

#### Lead contact

Further information and requests for source code, data or collaboration should be directed to and will be fulfilled by the Lead Contact, Solomon Brown (s.f.brown@sheffield.ac.uk).
Materials availability
This study did not generate new unique reagents.

Data and code availability
- This paper analyses existing, publicly available data. The sources for the datasets are listed in the key resources table.
- The code supporting the current study has not been deposited in a public repository because they have been developed with support from a commercial partner. Requests for access may be made to the lead author, but will be subject to funder approval for the first 12 months following publication.
- Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request, subject to funder approval for the first 12 months following publication.

METHOD DETAILS

This method section is divided into sub-sections covering the agent classes in the model, each of which, together with other key features, is illustrated in the graphical abstract. 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.

Main agent
The main agent includes start-up actions, policy related data, and a number of functions used by multiple agents. In this section, we provide detailed functional descriptions and identify data sources used to parametrize the model. 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.

Fuel pricing
Petrol and diesel prices in the simulation are drawn from UK Government published monthly pricing data from January 1990 to October 2018 (UK Government: Department for Business Energy & Industrial Strategy, 2018b). The prices were stripped of Value Added Tax (VAT) and adjusted to 2018 GBP to reflect the un-inflated costs used elsewhere in the simulation; see Figure S1. 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 model ignores any elasticity in mileage with fuel price.

Electricity pricing
Electricity prices are fixed in the base model as shown in Table S1 and are reflective of typical consumer prices payable in the UK for different types of charging.

Emissions
Emissions from Petrol and Diesel cars are based on standard fossil/biofuel mixes at 2018 of 2203.07 kg CO₂/l and 2626.94 kg CO₂/l sourced from 2018 UK Government company reporting factors (UK Government: Department for Business Energy and Industrial Strategy, 2018).

EV emissions are calculated based on a common emissions factor for all charging using historic annual grid emissions to 2019 (UK Government: Department for Business Energy and Industrial Strategy, 2018) and reducing by 10% each year thereafter in line with UK Government projections. See Figure S2.

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 2020 (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 (UK Government, 2018), but we include here an overview of the key features.

Vehicle excise duty. Up until 2010, a single VED based on vehicle emissions was payable each year; increasing numbers of emission bands were added, with just 4 in 2001 but 8 by 2009, ranging from zero for a car with under 100gCO₂/km to £405/year for those with emissions over 255gCO₂/km. From 2010 a ‘Year 1’ VED was introduced payable on first registration. Initially cars emitting less than 140gCO₂/km paid nothing with those emitting over 255gCO₂/km 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 year. For cars registered after 2016, those with emissions under 100gCO₂/km continued with zero VED, all others were charged £140 per year.

Benefit-in-kind. BIK rates have also been used to incentivize 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 ‘BIK’ 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 increased 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 modeled 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.

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 total cost of ownership (TCO) are also calculated in this module.

Car types and models. A database of cars includes a range of models across all segments. AFVs are typically based on the parameters of a specific model sourced from (EVDatabaseUK, 2019). Petrol and diesel only cars are included in the form of generic vehicles with data sourced from (Parkers, 2019). All the cars included in the simulation, with examples of typical cars, are given in Table S2. 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 (Bloomberg, 2018), see figure S3. 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 S3 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 S3 also plots the forecast cost of 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. We speculate that this is expected due to cost reductions in the glider, resulting from mass production and design refinements, which are not modeled in this evaluation.
A margin index, used to determine the amount of advertising of each model, is also recalculated monthly. The details of this calculation are contained elsewhere in this STAR Methods.

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 dataset; this enables the manufacture of ICE cars to be stopped according to government policy.

**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 be introduced within the last 12 months. A BEV is upgraded by adding 50 km of range. In order to estimate the new battery pack size, the WLTP efficiency is adjusted down using a factor of -0.003 of the 50 km range increment based on the analysis in Figure S4. 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 on the market. The range-upgraded model is available to be upgraded further as required.

**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.

**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 (Anderson, 2000; Consultants, 2017; Baik et al., 2019).

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 1, with $M_{bt,t}$ constrained between the minimum and maximum margins, 8% and 20% respectively.

$$M_{bt,t} = \frac{(P_t - P_l)}{(P_u - P_l)} (M_h - M_l) + M_l \quad \text{(Equation 1)}$$

where:

- $M_{bt,t} =$ base profit margin at time $t$
- $P_t =$ sales price of model at time $t$
- $P_l =$ notional lower price limit (£5,000)
- $P_u =$ 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 (Baik et al., 2019) and the margin set according to Equation 2.

$$M_{nt,t} = M_{bt,t} \times \frac{F_{pt,t}}{F_t} \quad \text{(Equation 2)}$$

where:

- $M_{nt,t} =$ new power train model profit margin at time $t$
- $F_{pt,t} =$ 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.

**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 15,000 km, 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 \(1 + \mathcal{N}(0, 0.08^2)\) to give a variation where 99% of values fall within +/-25% of the unbiased value. In some case, see Table S3, 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 while others may receive negative information, and a few will have conflicting information. Index values (reliability and aspiration) are limited between 0 and 1.

**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.

**Charging agent**

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

1. Major Route Charging; typically Direct Current (DC) rapid units designed primarily for en-route recharging.
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.

**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 20 km and they cannot reach the destination without recharging. For planned journeys, i.e., those contained within the car owner’s weekly 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 20 km, meaning that, referring to Figure S5, by 2040 all journeys can be undertaken without running out of charge.

Equation 3 was used to determine the mean separation between chargers using data on number of locations and chargers sourced from ZapMap (ZapMap, 2018) and illustrated in Figure S5. 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.

\[
S_{r,t} = \begin{cases} 
N_{r,t} \times S_r \over f(t) & t<2019 \\
\max[S_m, G, S_{r,t-1}] & t\geq2019 
\end{cases} 
\]  
(Equation 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%
- \(S_r\) = total length of primary routes (50,240 km (Department for Transport, 2018))
- \(f(t)\) = estimated charger separation from Figure S5
- \(S_m\) = target separation of chargers (20km)

When a car reaches a rapid charger, a queuing delay is implemented with a probability as defined by Equation 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 hypothesized as having a mean of 15 min and standard deviation of 5 min.

\[
Q_t = k(\bar{x} - x_t) 
\]  
(Equation 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
- \(x_t\) = 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 5. A survey for Transport Focus (Transport Focus, 2019) indicates current (ICE dominated) motorway service area dwell time of 20 min, so this calculation aims to penalise charging durations of longer than 20 min.

\[
S_{r,t} = S_{r,t-d} - 0.1S_{r,b} \frac{d - 20}{10} 
\]  
(Equation 5)

where:

- \(S_{r,t}\) = Range satisfaction at time \(t\)
- \(S_{r,t-d}\) = 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

**Destination charging.** Destination charging is generally considered to be charging at locations where other activities are carried out. In this simulation, we include workplaces (more accurately the opportunity to charge while at work), social destinations such as sport facilities, entertainment venues and restaurants, and shopping destinations. In all cases this includes the availability of charging at public car parks (such as...
city centre parking for shopping) as well as the facilities themselves. While 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 (Morrison, 2019)), which are more suited to the average duration of a food shopping trip.

Figure S7, sourced from ZapMap data (ZapMap, 2018), 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 (Podpoint, 2020), and this rate of growth is expected to continue for sometime, supported, in some cases, by the UK government’s charger grant programme (OLEV, 2019). Based on Figure S7, the availability of charging at each of these locations is hypothesized as an asymmetrical sigmoid function describing the probability over time as illustrated in Figure S8. 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 S4 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’.

**Household agents**
This section describes functionality associated with households.

**Household classification and location.** The NTS (UK Government: Department for Transport, 2016) provides a social classification based on a set of ONS categories known as the ‘2011 Census Output Area Classification’:

- Rural Residents
- Cosmopolitan
- Ethnicity Central
- Multicultural Mets
- Urbanites
- Suburbanites
- Constrained City
- Hard Pressed

The ONS (Office for National Statistics, 2018) ascribe one of these categories 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$^2$, so this provides a very granular classification for households. While the NTS data does not provide postcode information for individual houses, data mapping each postcode to a local authority is available from the ONS, together with the latitude and longitude of the post-code centroid. Thus, by drawing random NTS households of the correct social classifications for the defined postcodes and assigning those the appropriate latitude and longitude, meaningful spacial plots of car-type ownership and associated electricity demands (aggregated from car owner to household and then to spacial area or social group) can be obtained. Figure S9 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) (UK Government: Ministry of Housing Communities and Local Government, 2019) contains data on households that are most likely to have access to on-plot parking and therefore off-street charging. Table S5 summarizes the data. This shows that about 60% of households could theoretically have access to home charging, while 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 S6 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-story detached and semi-detached houses; these were allocated in the percentages shown in the ‘NTSAloc’ 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 WHS total in Table S5 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 while at home.

Households are assigned home charging capability based on the probability in Table Table S6 at the start of the simulation and are assumed to adopt home charging on purchasing an EV.

**Car owner agents**

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

**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 S10. 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 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.

\[ C_{ij} = k f(l_i) \times \frac{S_{ij}}{S_j} \]  

(Equation 6)

where:

- \( C_{ij} \) = monthly car budget for car owner i in household j
- \( k \) = constant to adjust budget to UK average
- \( l_i \) = monthly household income of household j
- \( f(l_i) \) = fraction of household income - see Figure S11
- \( S_{ij} \) = annual km travelled by owner i in household j
- \( S_j \) = annual km travelled by all car owners in household j

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). While there is data available on average savings of UK individuals (Financial Conduct Authority, 2017), 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 (Autotrader, 2019), with the average price of a new car substantially more at £33,559 (Car Dealer Magazine/CAP HPI, 2018). 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.
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.

**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 elsewhere in STAR Methods. 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 S4). 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 range knowledge index is used to set the car owners range requirement.

**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 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 (Noel et al., 2019). These drivers are assigned a minimum range of 600 km and target range of 1000 km, 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 1000 km.

**Other drivers.** For non-range-rhetorical drivers, the target range is set according to Equation 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.

\[
R_t = \min[(S_n(2 - K_t) + S_c, R_{mt})] 
\]  
(Equation 7)

where:

- \(R_t\) = target range (km)
- \(S_n\) = non-stop driving distance (see below)
- \(K_t\) = charging knowledge at time \(t\)

\(R_{mt}\) = maximum target range (km)

\(S_c\) = charging knowledge at time \(t\)
Non-stop driving range. The desired non-stop driving range for a driver was determined from an RAC survey (RAC, 2019) which gives the maximum driving times for a sample of 1,010 drivers. UK Department for Transport statistics (Department for Transport, 2019) indicate free-flow average car speed of 68mph (109kph) on motorways and 50mph (80kph) on single carriageway national speed limit roads. Thus, the times were converted to a distance assuming a speed of 100kph on the basis that these were typically primary route drives; see Figure S12.

Comfort margin. Each driver is further assigned a range comfort margin based on the work of Franke et al. (Franke et al., 2012). This indicates a psychological comfort margin in the range 5 to 200 km, with a mean of 19.2 km and standard deviation of 15.3 km.

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 8, 9 & 10, where:

\[ R_m = \min\{2S_{wm} + R_c, R_{m,t}\} \]  
(Equation 8)

\[ R_m = \min\{4S_{wm} + R_c, R_{m,t}\} \]  
(Equation 9)

\[ R_m = \begin{cases} R_{m,t} & K_t = 0 \\ \min\left[\frac{S_w}{K_t} + R_c, R_{m,t}\right] & K_t > 0 \end{cases} \]  
(Equation 10)

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

Car owner homophily and agent connection process
All household members are connected and thereafter additional connections are made based on a 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 ‘greenness’, children and gender are also included in the homophily index. The greenness parameter is determined based on the work of J. Anable (Anable, 2005). Drivers are randomly assigned to a type according to the probabilities in Table S7. Each driver is then assigned a greenness index based on a uniform distribution between the lower and upper thresholds shown in Table S7, corresponding to percentage range of driver types. A further function scales the greenness of each driver to limit it to a maximum value set for all drivers. This is
designed to enable car owner greenness 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 3 km of each other being assigned a similarity of 1 and from 3 to 6 km, 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 greenness 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 if agents in the model is illustrated in Figure S9. The Grannis Factor (Grannis, 2010) 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.

Needs weights and thresholds

Overall satisfaction and co-variance is determined from a weighted average of existence, social, and personality needs. In the absence of survey data, the weights for each car owner were randomly assigned using a Pert distribution for each as shown in Table S8. The selection of these values was based on delivering a reasonable match to real world parameters, such as car ownership durations.

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 optimization were correlated to the consumat’s income and education. This is based loosely on work by Morton et al. (Morton et al., 2016) 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.

Consumat agents

In these sections we describe the functionality of the consumat agents, each of which is permanently linked to one car owner and acts as its decision-making agent.

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, 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 Table S9, 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.

**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 S10 to produce an index between 0 and 1. For example, the existence need component for Reliablity 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 owner’s current car to the minimum, maximum and simple average of their peer’s cars, returning an index using a sigmoid function. A weighted mean, using the weights shown in Table S10, is generated for each need and these are combined in a further weighted mean to produce an overall satisfaction.

A weighted mean of the covariance data from the aggregate arrays is also generated for each need and combined in a further weighted mean, using the same needs weights as for satisfaction, to provide the overall variance measure, or uncertainty, in the information being received by the consumat.

These overall satisfaction and covariance variables are used to trigger state transitions of the consumat according to their individual satisfaction and uncertainty thresholds.

If a car owner’s car is written off or they dispose of the car due to budget constraints, the agent’s satisfaction index is reduced to zero resulting in a deliberation or optimization.

**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.

**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 the state evaluation.

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 peers’ 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.

Optimization: Unsatisfied and uncertain. ‘Optimizers’ are cognizant of both their peers and media information they have received, but do not carry out a full evaluation of all vehicles available. The following steps occur for an ‘optimizing’ 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 owners 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 the state evaluation.

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. Optimizers 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 maximize their satisfaction index across all vehicles available in the market, while taking into account social preferences. The following steps occur for a ‘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, based on data from Table S2.

5. The expected Existence Need and Personality Need satisfaction indices are set by comparison of the car to all cars in the market as per state evaluation.

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.

**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.

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

**Journey Functions.** Figure S13 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 (Lee, 2019) 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’ event pending, which results in a transition to ‘Breakdown’ state, or be written off due to an accident causing a transition to ‘Scrapped’ state. The rate of write-off is based on a 2017 survey by Churchill Insurance in the UK (Car Keys/Churchill Insurance, 2017).

On journey completion, all cars enter the ‘Parked’ state and chargeable cars (BEV and PHV) may then make further transitions. In the current 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 and cars will move into the holding state for that charging type as soon as they are ‘parked’. For this 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’.

**Energy costs.** A base fuel efficiency is defined for each vehicle as per Table S2. The actual fuel efficiency for each journey is determined from the mean journey speed (Lee, 2019). The cost of ICE refuelling is added to a monthly energy cost variable according to the current fuel price and fuel tax regime. The cost of in-transit recharging is added at the rapid charger rate, while charging at other locations is dependent on selected tariff. Each month, car refuelling/recharging costs are deducted from the car owners savings balance.

**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.

**Maintenance costs.** Car maintenance costs are set in the first year \(C_{m,0}\) from the value in Table S2. This figure is a function of the initial vehicle cost \(P_0\) and fuel train type according to Equation 11

\[
C_{m,0} = \begin{cases} 
C_{c,0} \times 0.01 & \text{carType} = \text{PET OR DIE} \\
C_{c,0} \times 0.015 & \text{carType} = \text{HEV OR PHV} \\
C_{c,0} \times 0.0025 & \text{carType} = \text{BEV}
\end{cases}
\] (Equation 11)

The actual maintenance cost is further limited between £60 and £900 per annum. These figures are based on indicative vehicle maintenance costs from (Maddy, 2016), 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 TÜV/Autobild survey data (TÜV/Autobild, 2017). Failure rates against distance and age are shown in Figures S15 and S16. It can be seen that up to 100,000 km, failure rate is dominated by car age, but beyond this, distance traveled also contributes. The data available does not disaggregate power train types, and while 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 12. The cost of the breakdown is set according to Equation 13, 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.

\[
\lambda_{s,t} = \begin{cases} 
0.0263t - 0.02 & s < 100,000 \\
0.0263t + 3.5 \times 10^{-7} s + 0.15, & s \geq 100,000
\end{cases}
\] (Equation 12)

where:

\(\lambda_{s,t}\) = failure rate (per year) at distance \(s\) and time \(t\)

\[
C_{m,t} = C_{m,t-1} + \frac{2U[0, C_{m,0}]}{\lambda_{s,t}}
\] (Equation 13)

Cars also undergo scheduled maintenance. The model assumes all cars are maintained annually or at 15,000 km 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.

**Car depreciation.** The value of each car in the model was depreciated according to Equation 14.

\[
C_t = \begin{cases} 
t < 1 & tD_{y,1}C \\
D_{y,1}C + (t - 1)D_{m}C - k(s_m - s_0) & t \geq 1
\end{cases}
\] (Equation 14)

where:

\(C_t\) = depreciation at time \(t\) (years)

\(D_{y,1}\) = year 1 rate of depreciation

\(D_{m}\) = rate of depreciation from year 1 onwards

\(C\) = cost of car when new (GBP)

\(k\) = odometer adjustment factor (0.06GBP/km)
Each car in the model has a different depreciation rate which is based on figures for similar vehicles from (Parkers, 2019). 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%.

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 Eq. 15. 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.

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

(Equation 15)

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 S17 illustrates how the aspiration index would vary with car age for two ICE cars and two BEV cars.

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 completion events in the associated car agent. The battery agent also triggers the transition to the ‘LowSoC’ event for its parent car.

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 (Lee, Yazbeck, and Brown, 2019) 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 20 km range (based on efficiency) and initiates a search for a rapid charger

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 a 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.
Stop driving. At the end of each drive, the car agent will initiate a 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.

Battery degradation. A simplified battery degradation function, based on a review of reported degradation rates (GeoTab, 2020) is employed as per Equation 16. Although battery degradation is not linear, in practice, it appears that manufacturer’s leave capacity headroom such that initial accelerated degradation is not visible to car owners and as such a large number of battery cycles can be completed before degradation becomes apparent.

\[
E_t = \begin{cases} 
  E_0 & \text{if } C_t < C_0 \\
  E_0 - D(C_t - C_0) & \text{if } C_t \geq C_0 
\end{cases} \tag{Equation 16}
\]

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 500
- \(E_0\) = energy capacity when new
- \(D\) = degradation rate (set at 0.003kWh/cycle)

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. While charging is in progress, an event scheduled at the end of every 30-min trading period updates an energy total and household demand (if charging at home). These totals are aggregated by the main agent for reporting purposes.