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Exploring the value of electric vehicles to domestic end-users

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ABSTRACT

Owing to the recent ban on the sales of new petrol and diesel cars in the United Kingdom (UK) by 2030, combined with the UK's commitment to net-zero emission of greenhouse gases by 2050, a projected increase in the growth rate of electric vehicles (EVs) is inevitable. In recent years, there has been an increase in the adoption of EVs, but not at a rate sufficient to meet net-zero targets. Although benefits do exist for current EV owners, barriers such as the availability of charging infrastructure, total cost of ownership, battery costs, amongst others still present a challenge for the required adoption rate. In this work, we therefore aim to address some of these barriers, specifically the total cost of ownership and battery costs, by exploring the value a range of EVs on the market give to domestic end-users with different usage classes. Using a techno-economic-environmental mixed integer linear optimisation model which considers local energy demands, retail electricity tariffs, local renewable energy generation and battery degradation, potential benefits for EVs adopters are analysed from a cost or Carbon dioxide (CO_2) minimisation objective. This model adopted considered a range of vehicle types – EVs and non-EVs – and properties, installed PV sizes, and user travel behaviour classes, and results showed that although EVs have a relatively higher purchase costs, total cost values are comparable, in some cases cheaper, when compared with conventional non-EVs. EV users further gain from environmental benefits through a reduction in the CO_2 emitted irrespective of the user's desired goal. A dominance analysis was also carried out to determine the order of importance of key input variables to the optimisation model in predicting costs and CO_2 emission quantities. The results obtained are helpful to end-users in prioritising EV features during purchase based on personal goals of cost or carbon emissions reduction.

1. Introduction

The potential impacts and associated risks of climate change, and the role greenhouse gas (GHG) emissions play, have been acknowledged in most parts of the world. Eleven countries (the United Kingdom, UK, being the first major economy in the world) have thus set a net-zero GHG emissions target by 2050 (Committee on Climate Change, 2019). Amongst sectors in the UK, the transport sector has been identified as the largest contributor to GHG emissions (Fig. 1). As such, one of the scenarios outlined by the UK government to achieve net-zero targets involves extensive electrification, particularly of transportation and heating (Committee on Climate Change, 2019; Küfeoğlu and Khah Kok Hong, 2020). This directly involves a transition to electric-powered surface transport vehicles.

Prior to this policy publication by the UK government, there has been a growing adoption (and still is) of Electric Vehicles (EVs) (Fig. 2). Amongst the currently available EV types – Battery Electric Vehicle (BEV), Hybrid Electric Vehicle (HEV) and Plug-in Hybrid Electric Vehicle (PHEV) – there has been a minimum growth rate of 28% year on year between 2014–2019. This has been attributed to benefits from capital subsidies, lower fuel and vehicle taxation as well as the increasing cost-competitiveness of EVs in comparison with traditional internal combustion engine-type (ICE) vehicles. In addition to this, the announcement in November, 2020 by the UK government, of the ban on the sales of new petrol and diesel cars and vans after 2030, and hybrid car sales after 2035 (Department for Business Energy & Industrial Strategy, 2020b), is projected to cause an increased growth rate in the coming years, especially for BEVs, amongst other factors (Lee and Brown, 2021a).

This projected growth has its impact on the power grid. Unregulated connections of EVs can result in a substantial increase in aggregate demand, impact power quality, or cause an outright destabilisation of the grid (Ahmadian et al., 2020; Xiong et al., 2017). However, benefits do exist to the grid as well as to the vehicle owners. EVs can act as additional energy storage devices providing energy via vehicle-to-X (where X is home (H), building (B) or grid (G)) technologies (Tchagang and Yoo, 2020). This allows for peak load shaving, reduction in household/building energy costs, ancillary service provision and backup power supply during outages. What then becomes important is

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Abbreviations/Acronyms

The abbreviations and symbols used are defined as follows:

2WP	Two-way power
ABM	Agent based model
AF	Availability fraction
BEV	Battery electric vehicle
DIE	Diesel engine vehicle
EV	Electric vehicle
ICE	Internal combustion engine
Li-ion	Lithium ion
PbA	Lead acid
PET	Petrol engine vehicle
PV	Photovoltaic cell
SOC	State of charge
UK	United Kingdom

the availability of an optimal scheduling strategy to ensure that these benefits are leveraged whilst minimising the negative impacts to the grid.

To this end, several studies have focused on leveraging such benefits from the grid point of view using a collection of optimisation techniques. Optimisation techniques are used as they determine (through proven mathematical theory) the best decisions that can be taken for any defined system. By setting a system goal (called an *objective*) and defining the system through mathematical equations with known limits (called *constraints*), the solution to the mathematical equations can be obtained through proven techniques which yield the best course of action towards achieving the pre-defined goal. Das et al. (2020) used such technique when they proposed a multi-objective techno-economic-environmental optimisation strategy for EV scheduling. Some of the system goals (objectives) considered were the minimisation of electricity cost, battery degradation, grid interaction and CO_2 emissions in a home-micro-grid context, with provision of frequency regulation services. The resulting mathematical model was applied to a single household and a UK district network using projected assumptions of photovoltaic cell (PV) and EV penetrations in 2040 under different scenarios. This method was further improved on by Das et al. (2021) to account for real-time operations of decentralised EVs. The multi-objective model was solved via dynamic programming as opposed to a hierarchical process adopted previously to obtain real-time optimal schedules for the EV with fixed availability periods.

Wang et al. (2020) looked into the economic benefits of EVs versus stationary energy storage devices for PV systems. EV availabilities of 90% and 100% were assumed under PV cell sizes ranging from 1–6 kWp studied in three locations in the UK. Amongst their findings, the study showed that the time in which an EV is available has an impact on the benefits realisable especially when paired with a PV generating system. Economic benefits were also found to vary with location.

Merhy et al. (2021) proposed a multi-objective optimisation approach which focused on the charging process for electric vehicles providing X-to-vehicle (X2V) services. The objectives included maximum the battery's life cycle, minimising battery costs, load levelling and fulfilling the energetic needs of the EV related to infrastructure. The model was solved using a genetic algorithm under different scenarios with set preferences for each objective. Tchagang and Yoo (2020) also proposed a multi-objective optimisation approach for EVs in a V2G system used for peak-shaving and frequency regulation. Objectives considered were to minimise building owners energy costs as well as the battery degradation whilst providing V2G services at particular times in a day. Fixed EVs battery capacity sizes were also used with a fixed usage profile under different SOC ranges. Results showed that EVs reduced the overall electricity bill especially in the state of charge (SOC) range of 30%–90%. In Alilou et al. (2020)'s study, the proposed multi-objective algorithm was applied to a residential smart micro-grid with objectives to minimise the community's electricity bill and peak demands. Real-time tariffs, as opposed to wholesale prices in previous studies, were used with the option of the smart home selling electricity back to the grid. A smart home here refers to home consisting of appliances, renewable distributed generation and EV, all controllable by a home energy management system. With a case of 20-smart homes, each with a fixed EV type and property as well as a fixed PV system size, results showed that both the energy bill and peak demand of the community were reduced. The stochastic nature of PV generation and EV availability and use were modelled using a combination of Latin Hypercube Sampling (LHS) and K-means clustering to generate PV generation and EV availability profiles. Lu et al. (2020) adopted a Monte Carlo simulation instead for EV demand profiles for a similar study.

In each of these studies, a fixed EV type and property (battery capacity, power, etc.) are mostly assumed with a fixed vehicle availability profile. As there are a range of EVs currently on the market with each user having different travel behaviours, relating results to most vehicle users becomes difficult. A great deal of emphasis has also been on the grid's perspective – provision of ancillary services and/or with access to the wholesale market prices – which individual users have little or no control of or access to. There has also been studies on the potential benefits to individual users with access to the retailer electricity market. Amongst others, Aguilar-Dominguez et al. (2020) used a techno-economic optimisation model to assess the potential economic benefits EVs had on minimising an individual user's electricity bill. Two EVs were used as a case study with a single user travel profile. Results showed that under all electricity tariffs considered, EVs using V2H technologies provided additional savings to the household. EV, PV and/or battery costs were however not considered in the optimisation model. As with most other studies, bi-directional charging (i.e. two-way power, 2WP, feature) was assumed for EVs, which currently is not the case for most BEVs and PHEVs on the market.

A study has already shown that the current adoption rates of BEVs is insufficient for the UK transport sector to achieve the 4th to 7th carbon budgets (Küfeoğlu and Khah Kok Hong, 2020). The carbon budgets are a result of a Climate Change Act in the UK which guides the government in achieving the 2050 carbon emissions reduction target over a five-yearly period. By this act, the UK is required to achieve a 51% reduction (for 2023–2027; 4th carbon budget) and 68% reduction (for 2038–2042; 7th carbon budget) from 1990 emission levels in order to achieve 2050 net-zero goals. Kumar and Alok (2020) published a review identifying key motivators and barriers towards EV adoption. Key motivators included the potential environmental benefits, availability of incentives and advantageous government regulations, and the symbolic attributes amongst others. Barriers included the availability of charging infrastructure, the total cost of ownership, battery cost and technology, vehicles design and features, range anxiety, etc. Kumar and Alok (2020). Lee and Brown (2021a) also presented an agent based model (ABM) to simulate the uptake of EVs considering socio-economic motivators. However, it becomes important to use the range of techno-economic-environmental tools available to study the potential benefits these EVs can provide based on their type and the users' travel behaviour/profiles in order to address some of these adoption barriers for potential domestics EV adopters.

To this end, we intend to study a range of EVs on the market matched with differing user travel profiles to present results on the economic and environmental benefits in a format that a range of UK users can relate to. This study addresses the barrier of total cost of ownership to EV ownership whilst emphasising the potential environmental benefits. This study is not aimed at predicting future behavioural trends for EV adopters as investigated by other researchers (Lee and Brown, 2021b). In a previous study (Aguilar-Dominguez et al., 2021), we proposed a machine learning model to predict the location and

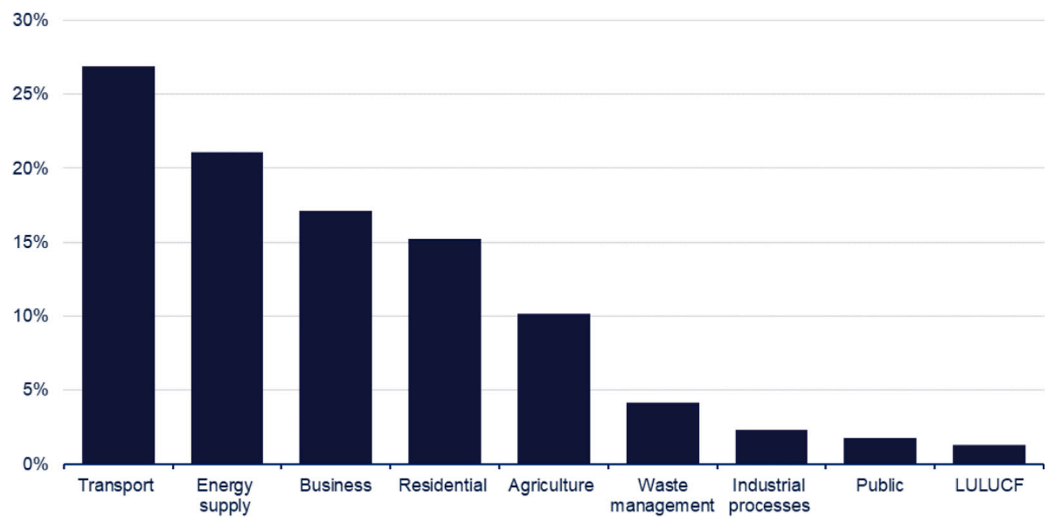


Fig. 1. UK greenhouse gas emissions; 1990–2019 (Department for Business Energy & Industrial Strategy, 2020a).

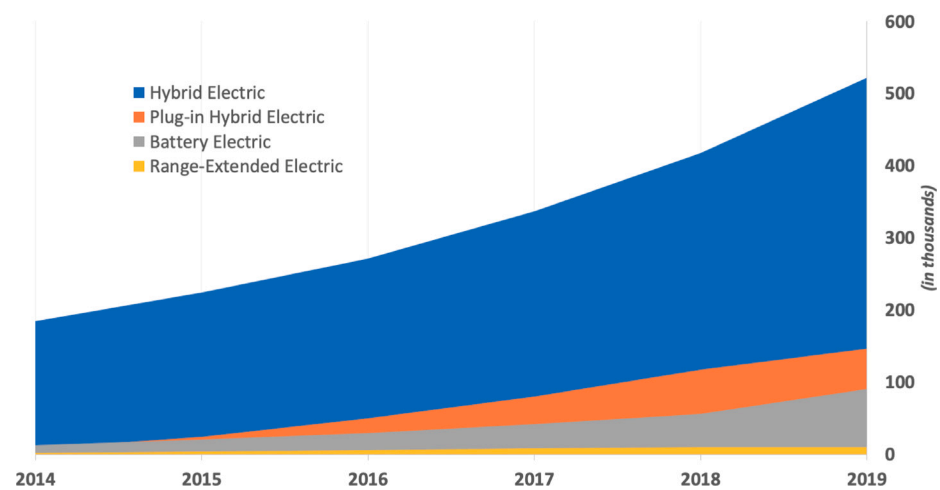


Fig. 2. UK EV adoption; 2014–2019 (Department for Transport, 2020b).

distance travelled of an EV over a period of time based on the UK National Travel Survey (NTS). There, we considered a specific electric vehicle providing V2H services with a fixed PV cell size over a range of user travel profile groups classified according to the ratio of vehicle availability over a period. In this study, we expand on that work considering a range of vehicle types and models having different properties, PV sizes, and the inclusion of degradation constraints to better represent battery performance for a user within a longer time period. Using a techno-enviro-economic optimisation model, we present results obtained for a range of vehicle use cases, vehicle types (EVs and conventional ICE vehicles), installed PV array sizes, and electricity tariffs, to compare the economic and environmental benefits. An optimisation model is adopted to deterministically obtain the best set of decisions for the system in question.

The main goal of this work is to identify and quantify the benefits (economic and environmental) EVs can render to domestic end-users, whilst identifying the key factors that affect the level of such benefits. This we achieve through the following contributions:

- the presentation of a techno-enviro-economic optimisation model for the optimal scheduling of electric vehicle charging/discharging considering battery degradation, local renewable energy generation, vehicle travel patterns, and a set of electricity tariffs;
- to show the benefits – economic and environmental – that users can/cannot derive from different system configurations based on individual combinations of:
  - vehicle types — BEV, Petrol-based (PET) and Diesel-based (DIE) conventional vehicles;
  - installed PV system sizes;
  - vehicle availability profiles.
- compare the economic and environmental benefits BEVs with and without 2WP features provide to individual users under different installed PV system sizes and infer optimal configurations per user class;
- to identify the key properties that significantly contribute to total cost, electricity cost and CO_2 emissions.

The rest of this paper is structured as follows. In Section 2 we present a case study having a diverse range of vehicle types, EV use profiles, PV cell sizes, and domestic user goals (minimal cost or CO_2 emissions). The results from our analysis of the case study are also discussed. The analysis involved solving the optimisation model proposed in Appendix for the optimal operation of EVs and processing its results. A summary of our findings are given in Section 3.

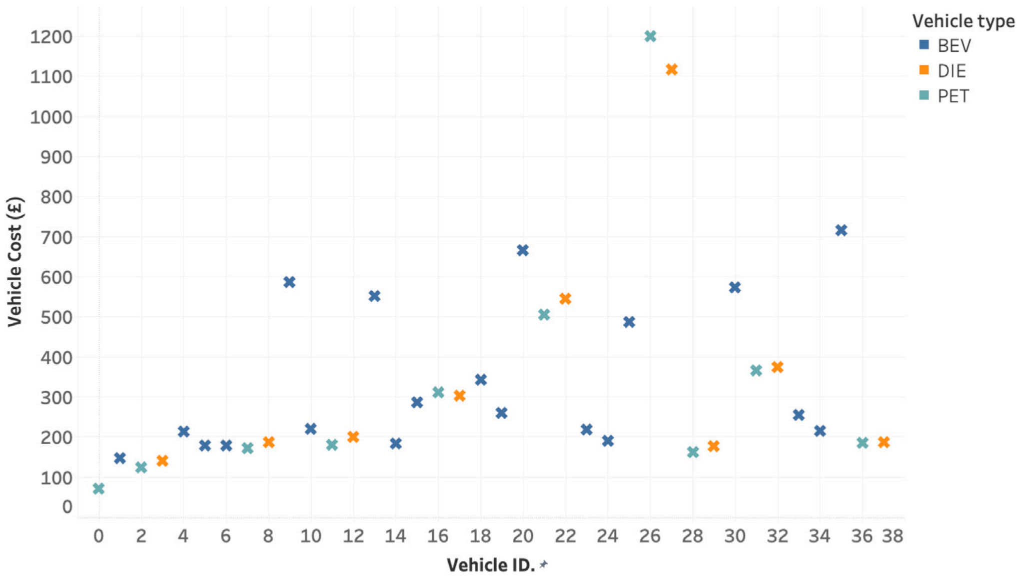


Fig. 3. Monthly vehicle cost distribution.

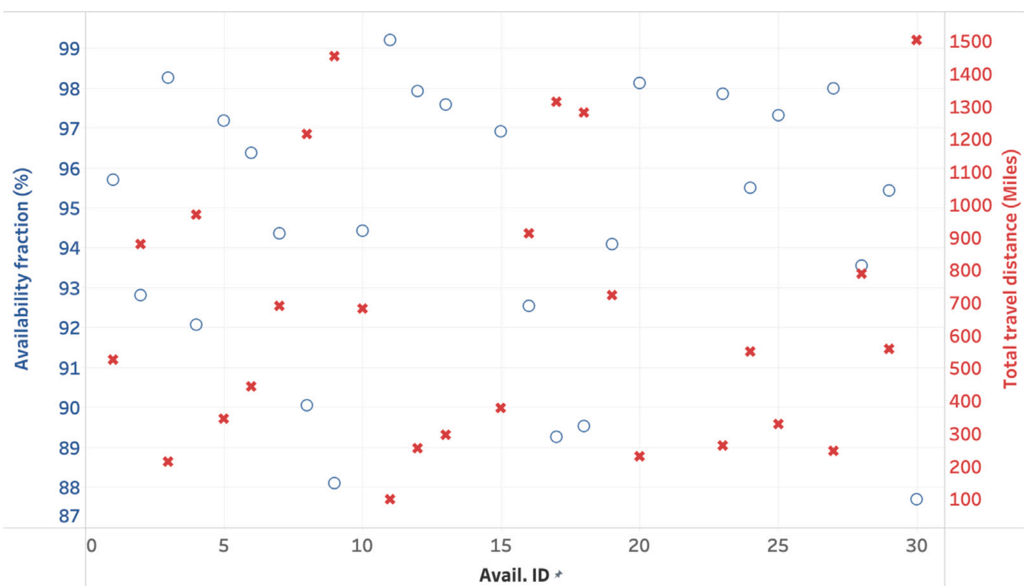


Fig. 4. Vehicle availability fraction.

2. Case study

The proposed optimisation model (described in detail in Appendix) was applied to study the potential benefits for a range of vehicle types, user travel behaviour profiles, electricity tariffs and PV cell sizes for a domestic UK customer under two different objectives — obtain the least cost (Cost minimisation objective) or least overall environmental footprint (CO_2 minimisation objective) for the user.

Thirty-eight vehicles of different types — BEV, DIE, PET, currently available on the market were analysed, with known properties such as the purchase cost, maintenance cost, fuel consumption, range, CO_2 emission, tank size; and battery capacity, energy consumption during travel and output power if an EV. In some cases, and based on actual vehicle features from the manufacturer, EV have the two-way (2WP) feature. This enables the EV to participate in Vehicle-to-Home/Grid (V2H/V2G) services, providing electricity back to home/grid thus acting as an energy storage device. CO_2 emissions are calculated as the net contribution of grid-imported power (based on the generation mix at the time of electricity use) and the tail-pipe CO_2 based on the vehicle model considered. Fig. 3 shows the purchase cost distribution of each vehicle considered per type.

Using data from the UK National Travel Survey (UK Government Department of Transport, 2018), a set of user travel data over a period of a month were obtained. UK National Travel Survey analysed when, where and why vehicles user's travel over a period of time. A total of 30 travel data sets were selected for use for this case study including users who travel short and long distances. Fig. 4 shows the total travel distance in miles and the availability fraction (AF) for each vehicle. The AF is defined as the fraction of the total time in which the vehicle is located at home.

Local electricity load profile for a typical domestic household was generated using the ELEXON profile class 1 10-year average (ELEXON, 2018). This corresponds to the profile class for domestic unrestricted customers in the UK, and represents their pattern of electricity consumption. Random noise based on a uniform distribution was added to the load profile averages to obtained a unique load profile for

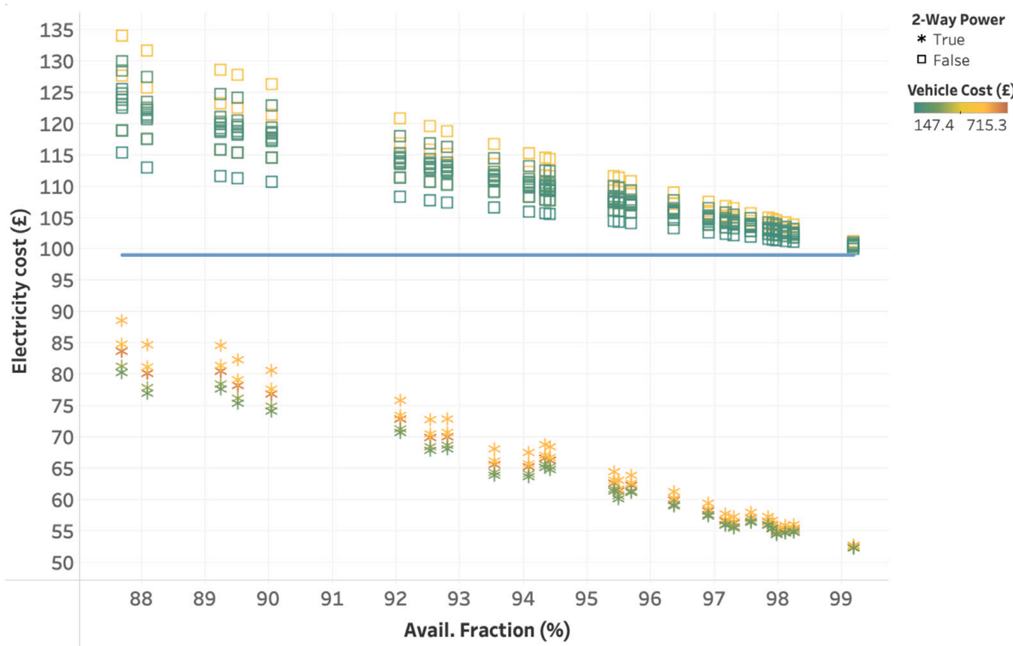


Fig. 5. BEV: Monthly electricity cost vs vehicle usage; No PV.

the month of January, 2019. Two electricity tariff options were also made available to the optimisation model — a flat and a time-of-use based tariff. The flat tariff had a standing charge of 20.39p/day and variable charge of 14.53p/kWh. For the time-of-use tariff, the Octopus GO tariff (Octopus Energy, 2020) for EV owners was adopted with a standing charge of 25p/day, an export price of 5.5p/kWh, peak charge of 14p/kWh and an off-peak (00:30–4:30) charge of 5p/kWh.

Solar generation was obtained from the PVGis platform (Joint Research Centre, 2020) for a location in Finningley, Doncaster, UK for installed PV cells of ratings 1 kWp, 2 kWp, 3 kWp, and 4 kWp.

Using the datasets described above, the proposed optimisation model was solved for each vehicle type, user travel profile, installed PV cell size and model objective (min. Cost and min. CO_2 emissions), totalling 11,400 cases. These were all implemented using Pyomo 5.6.8 (Bynum et al., 2021; Hart et al., 2011) and solved with Gurobi 9.0 solver (Gurobi Optimization, LLC, 2021) to global optimality using an Intel Xeon E-2146G with 32 GB and 12 threads running Windows 10. Each run solved with a minimum, average and maximum CPU time of 1.4 s, 2.8 s and 20.1 s respectively and the results obtained are analysed below.

2.1. Cost minimisation objective

2.1.1. Electricity cost

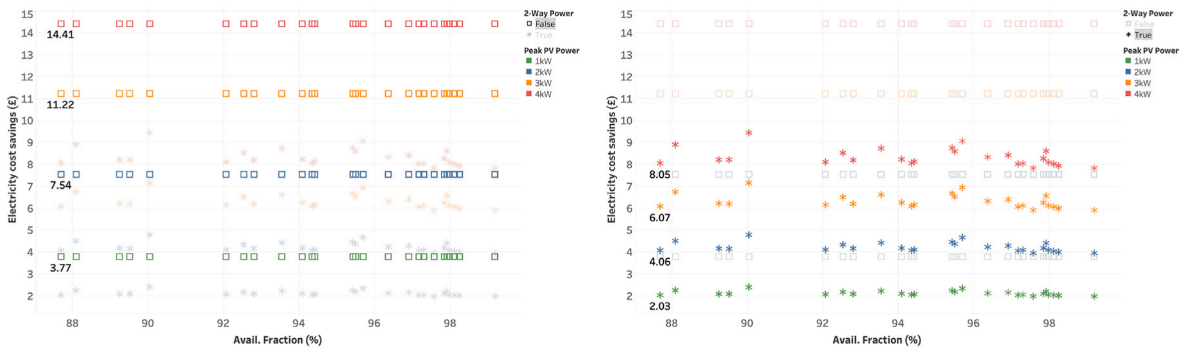
Fig. 5 shows a plot of the net electricity cost (in £) of the household for different BEVs under a range of user profiles, ordered by their availability fractions for a case with no installed PV. A noticeable difference in electricity cost is observed for BEV with the 2WP feature, with as much as a 48% reduction when compared with those without this feature. This is as EVs with the 2WP feature enabled, may also serve as an energy source at periods of high electricity prices and demand, reducing the overall electricity costs.

The blue line indicates the base electricity cost. This corresponds to the minimum cost obtained by the household when strictly satisfying the household energy demand alone (without an EV). Irrespective of the frequency of travel by BEVs with 2WP, a reduced electricity cost was realised for all vehicles considered. This meant that for all BEVs with 2WP considered, the domestic user always realised an electricity cost saving no matter how frequently the user travelled. As expected, BEVs without the 2WP feature increased the overall electricity cost owing to an increased overall energy demand for travel. The additional cost for use cases with low AFs was somewhat comparable with the base household electricity cost.

A somewhat linear negatively-correlated trend is observed between electricity cost and AF for BEVs without 2WP, with a clearer spread between different vehicles when they are less available at home. This correlation is not as smooth for BEVs with 2WP, as in quite a number of cases, usage profiles with lower AFs cost less than their adjacent higher neighbours. This may be attributed to the fact that EVs with 2WP also act as an energy source and therefore the final electricity costs are affected not just by how frequently the vehicle is available at home, but also by the period it is. Hence, from an electricity cost perspective, the benefits realised from an EV with 2WP may be increased by further taking note of its particular times of availability.

An additional observation from Fig. 5 is on the relationship between vehicle cost and electricity costs. Generally, BEVs with a lower capital cost (shaded green) tended to have lower electricity costs, but the reverse is not the case for more expensive vehicles, and points to the fact that vehicle capital cost is not a key metric in predicting electricity cost savings for an EV owner.

Fig. 6 shows the electricity cost savings obtained by users under different installed PV cell sizes and availability fractions. The electricity cost savings are calculated with respected to the case with no installed PV. Fig. 6(a) shows the results for BEV without the 2WP feature for a 1–4 kWp PV. In each of the cases, the relative electricity cost savings were constant irrespective of AF of the vehicle usage profile. However, a diminishing electricity cost saving is observed per additional kWp of installed PV - £3.8, £3.7, £3.7 and £3.2 additional savings for a 1 kWp, 2 kWp, 3 kWp and 4 kWp PV cell respectively. This is because, for the 1–3 kWp PV systems, little (3 kWp PV) or no energy is sold back to the grid, but is instead used to reduce the local energy demands of the household. For the 4 kWp PV system, after local energy demands have been met, the excess renewable energy generated is exported to the grid at 5.5p/kWh (as the GO tariff was selected as optimal) - a rate much lower than prevailing import rates. Although these results were obtained for a PV system installed in Finningley, relocating the study to an area with higher solar irradiance will increase the cost savings, in a similar way to how increasing the PV array size was shown to do. Hence, given the current system setup, it is not beneficial for a domestic



(a) No 2WP

(b) 2WP

Fig. 6. BEV: Monthly electricity cost savings.

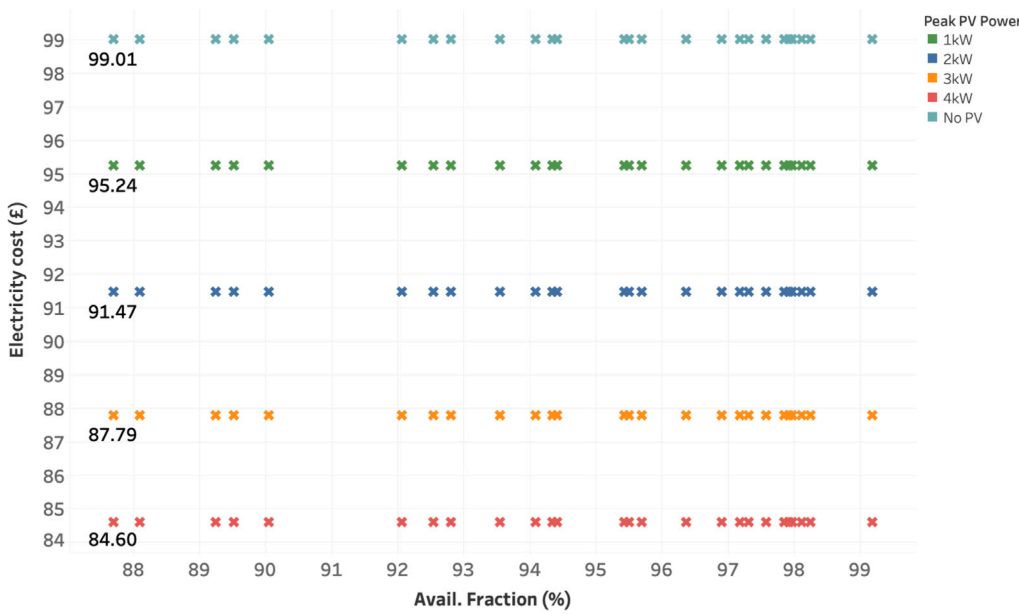


Fig. 7. ICE: Monthly electricity cost vs AF.

user to purchase a PV system with ratings greater than the household's peak energy demand unless a higher export tariff is offered.

Additional savings may be realised for BEVs without 2WP when solving strictly for a minimum electricity cost objective, but as the total cost was minimised, results show that a proportionate increase in electricity cost savings is not realised for each kWp increase in PV installed above the peak local demand. Although the net electricity costs for BEVs with 2WP are much lower than without 2WP, results still show that bigger sized PV cells are more beneficial (per kWp increase) to BEVs without 2WP from an electricity cost perspective.

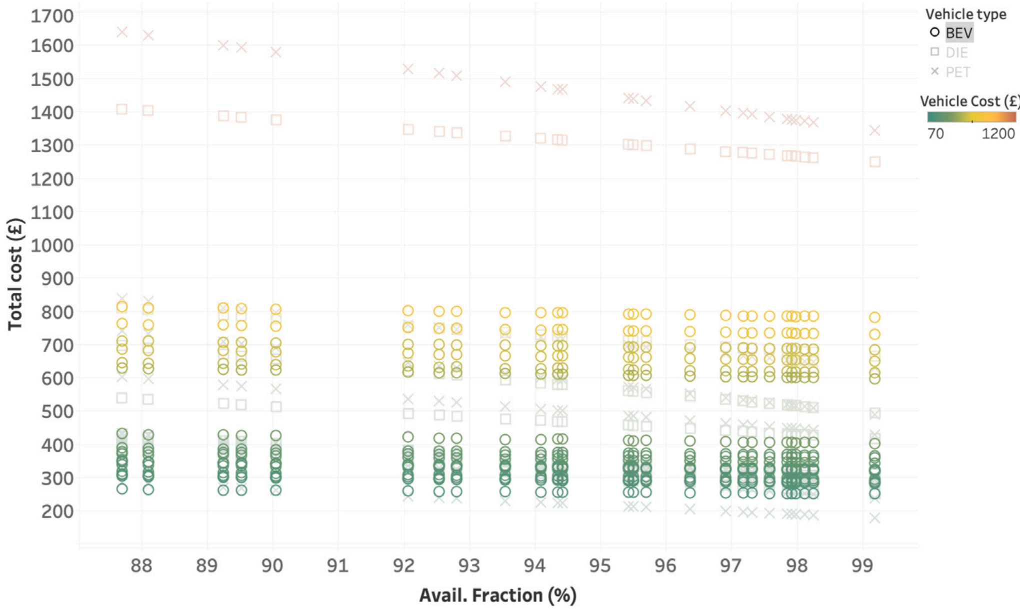
A similar trend can be observed for BEVs with 2WP (Fig. 6(b)), although with a lower electricity cost savings. Uncorrelated cost savings values are also observed per AF, still pointing to the fact that the time in which a BEV is available at home affects the cost for the user. Although the electricity cost savings for BEV with 2WP are smaller, it should still be noted that the net electricity costs are much lower when compared to BEVs without 2WP (refer to Fig. 5). Fig. 6 also shows that having a BEV with 2WP does not lead to a greater reduction in a user's electricity bill with larger-sized PV cells as compared to those without 2WP, with a total cost minimisation goal.

The electricity costs for non-BEV (DIE and PET) vehicles for different AFs are shown in Fig. 7. None of these vehicles require/supply electrical energy from/to the household, as such changes in vehicle use (AFs) had no effect on the electricity cost of the household. The values thus represent the minimum electricity cost realisable by the household without any storage device for the total cost objective. Values in turquoise blue correspond to the case in which no PV system was installed with a cost of £99.01. This is comparable with the electricity cost values of a BEV without 2WP and a high AF (low usage), but much higher than a BEV with 2WP for all considered usage cases as stated previously.

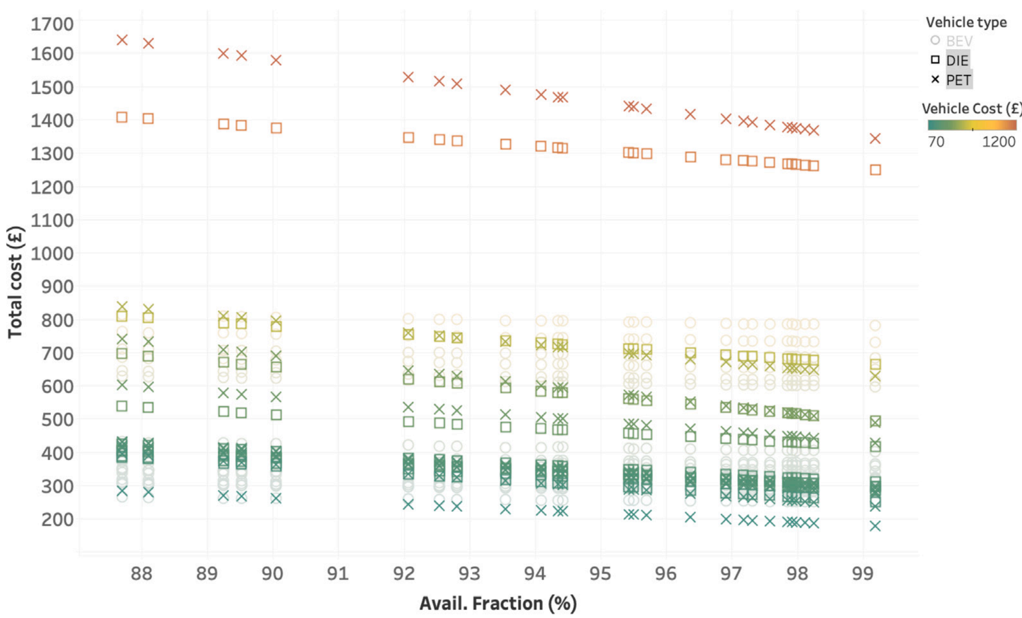
2.1.2. Total cost

Fig. 8 shows the results of the total cost for each AF and vehicle grouped by type. The total cost is calculated as the sum of the net electricity cost, purchase and maintenance cost of the vehicle, fuel cost (for PET and DIE type vehicles), and the purchase of the installed PV cell for the period of consideration. Fig. 8(a) shows the result for BEVs and Fig. 8(b) for conventional ICE-type vehicles. One thing easily observed from both figures is the degree of elasticity of total cost to AF each vehicle type shows — PET being the most elastic and BEV being the least.

An implication of this can be seen from observing the values at the bottom of each graph. Based on the vehicle cost distribution shown in



(a) BEV



(b) PET & DIE

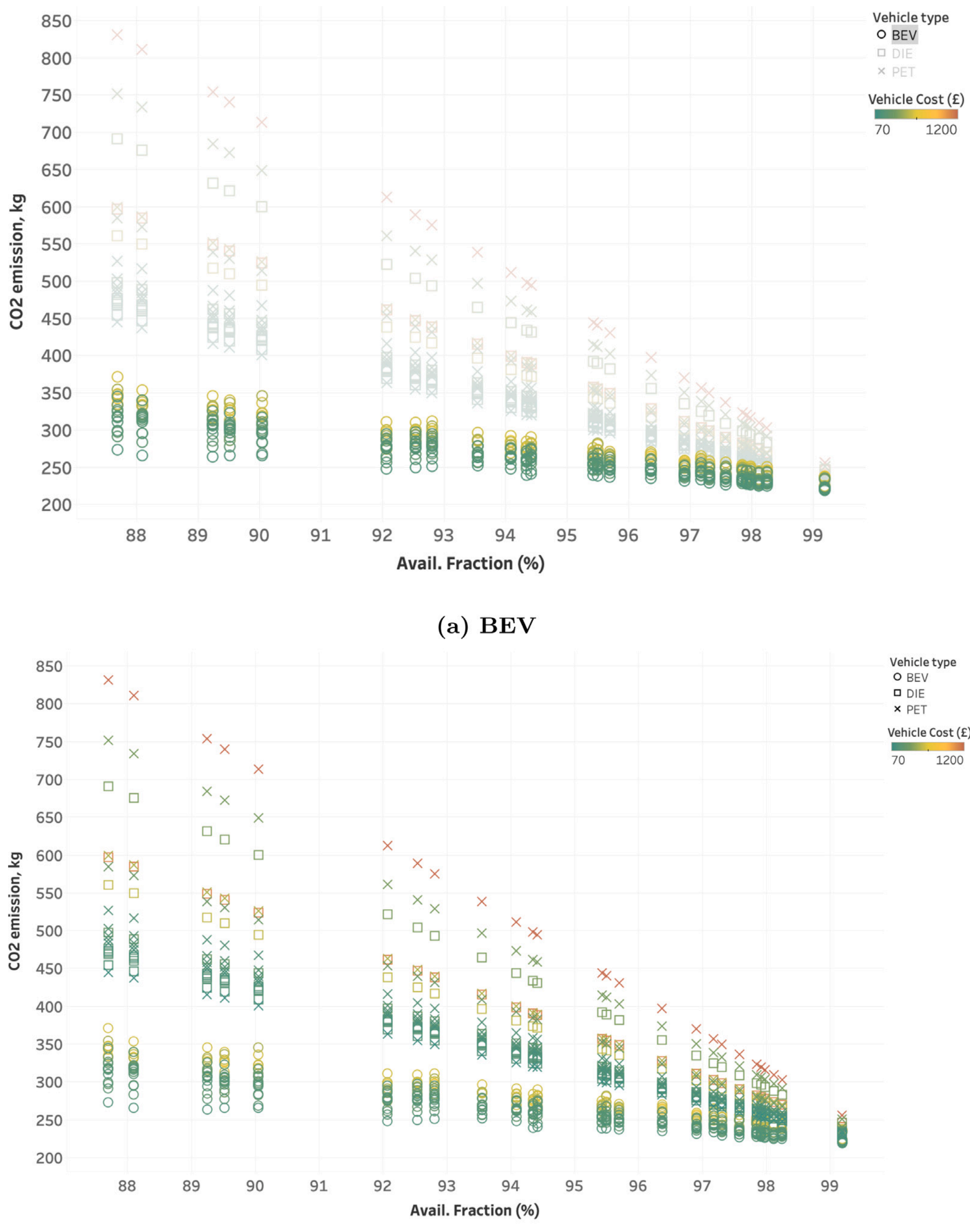
Fig. 8. Monthly total cost vs vehicle usage; No PV.

Fig. 3, it is correct to assert that the vehicle purchase cost contributes the most to total cost values, with the exception of the two cheapest vehicles (which are both PET vehicles). This can also be observed in Fig. 8. However, as the AF decreases, comparable total cost values are observed between PET and BEV vehicles from AF=90%, with the BEV becoming cheaper further down despite having a purchase cost which is double that of the PET (Fig. 3). This is also observed across other similarly-costing ICE–BEV pairs in the figure. Hence, BEV, though currently considered relatively expensive, in terms of purchase costs, are quite comparable in total cost values (and cheaper in some cases with increased vehicle use) to conventional ICE vehicles. However, much cheaper BEV vehicles will go a longer way in ensuring the same observation across all vehicle usage types, and encourage greater EV adoption.

It should also be noted that the two data clusters for the BEV shown in Fig. 8(a) do not correspond to BEVs with and without 2WP, as a mix of both types occur in each data cluster.

2.1.3. CO_2 emissions

Additional benefits realised from BEVs can also be seen from their total CO_2 emission results. Fig. 9 shows the results of the total CO_2 emissions for both BEVs (Fig. 9(a)) and ICE-type (Fig. 9(b)) vehicles in kilogrammes (kg) across different AFs. The total CO_2 emitted was the sum of CO_2 equivalent of the energy imported from the grid and that emitted during travel by the car. Quite clearly, for ICE vehicles, a linear trend is seen as the AF (and total distance travelled) increased as expected. The increase in CO_2 for BEV with AF decrease is attributed to the increase in electricity import owing to car charging requirements.



(a) BEV

(b) PET & DIE

Fig. 9. Monthly CO_2 emissions vs vehicle usage; No PV.

2.2. CO_2 emissions minimisation objective

All cases were solved again with a different goal for the domestic user. In the results presented below, the optimisation model was solved in order to realise minimal CO_2 emissions by the domestic user. Both model objectives were solved separately, instead of using a multi-objective approach as sometimes seen in the literature, to present findings on the extremes of use cases. As ICE-type vehicles (PET and DIE) cannot contribute to electricity reduction/increase or use such energy form directly, the results for the CO_2 minimisation objective are the same as those obtained for the cost minimisation objective.

2.2.1. Electricity cost

Fig. 10 shows the plot of the electricity cost versus AF for BEVs when no PV is installed locally. It is apparent that it costs much more to achieve a reduced CO_2 emission for the BEV. The figure shows that only BEVs with the 2WP feature and little or no travel achieved minimum CO_2 levels without additional electricity costs when compared to the base electricity cost without any form of storage (blue line). This occurrence at a high AF is similar to a case with a stationary energy storage device. There is a greater change in electricity costs for BEVs with 2WP as AF reduces. As the objective was to minimise total CO_2, the BEVs with 2WP acted to store energy at periods of low CO_2 equivalent emission from grid-imported power, and discharging at periods of high equivalent emissions irrespective of electricity price.

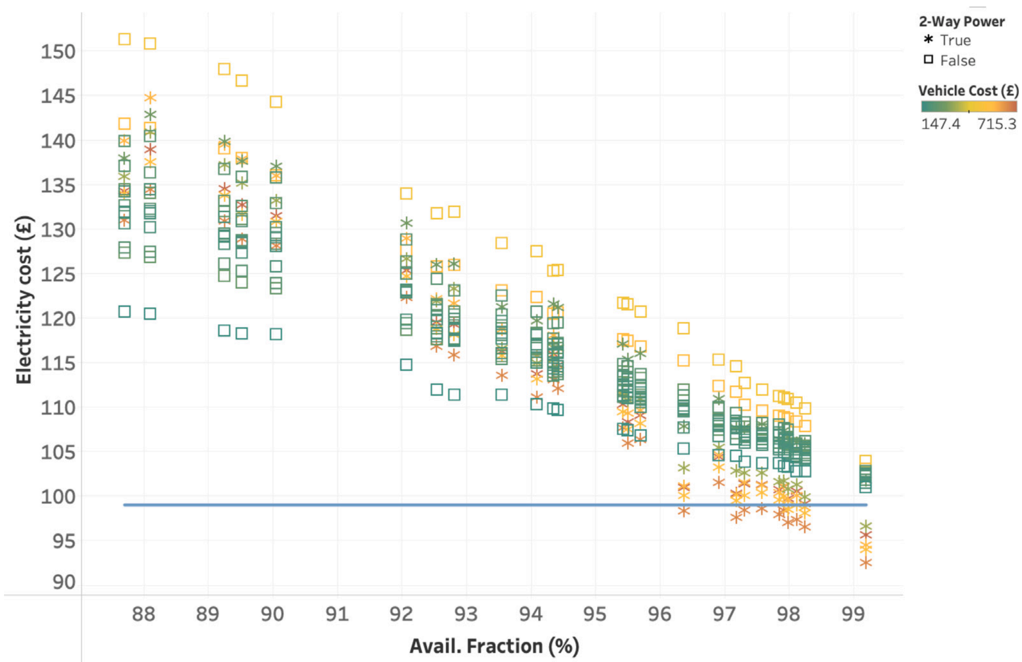


Fig. 10. BEV: Monthly electricity cost vs vehicle usage; No PV (CO_2 objective).

This translated to a reduced CO_2 emissions values by as much as 90kg for some vehicles.

2.2.2. CO_2 emissions

Fig. 11 shows the CO_2 emissions per AF for BEVs 11(a) and regular ICE vehicles 11(b). The two groups of data points shown in Fig. 11(a) also correspond to BEVs with 2WP (bottom half) and those without, showing that BEVs with 2WP clearly achieve a greater CO_2 reduction for the cases considered. Combined with the plot in Fig. 10 for cases with a high AF, the results also point to the fact that reduced CO_2 emissions can be achieved by a household with energy storage without a penalty on electricity costs.

2.2.3. Total cost

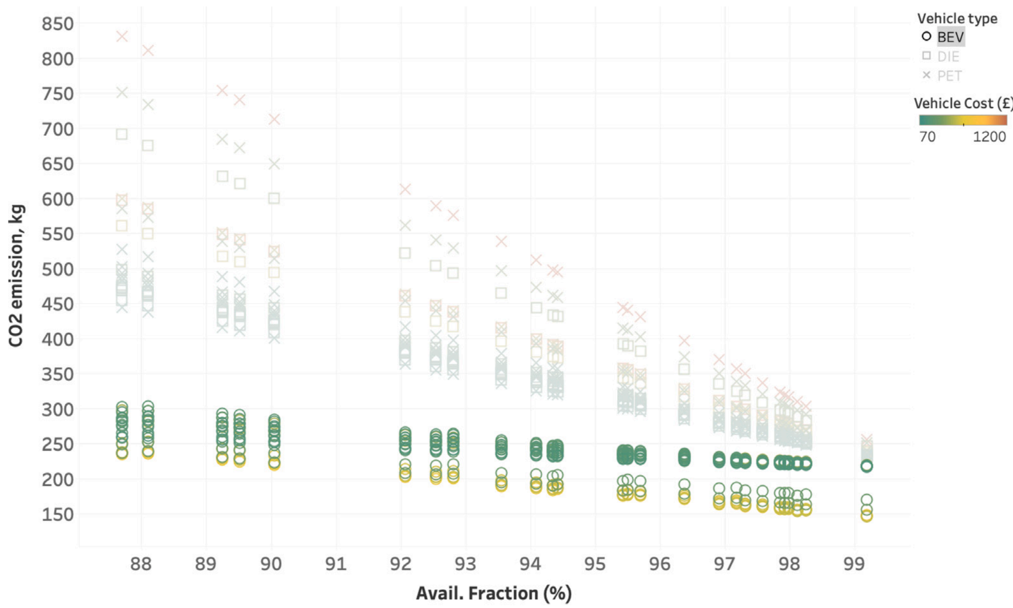
Total cost plots are also presented in Fig. 12 to understand the cost implication of a CO_2 minimisation objective. As stated earlier, the results for ICE-type vehicles are still the same from Section 2.1. These show that although total cost values for BEV increased, they still compare with conventional ICE vehicles especially with cases of high vehicle use (low AFs). Hence, BEVs, especially those with 2WP, present a cost competitive case irrespective of the vehicle owners desired goal — minimise cost or reduce overall carbon footprint.

2.3. Dominance analysis

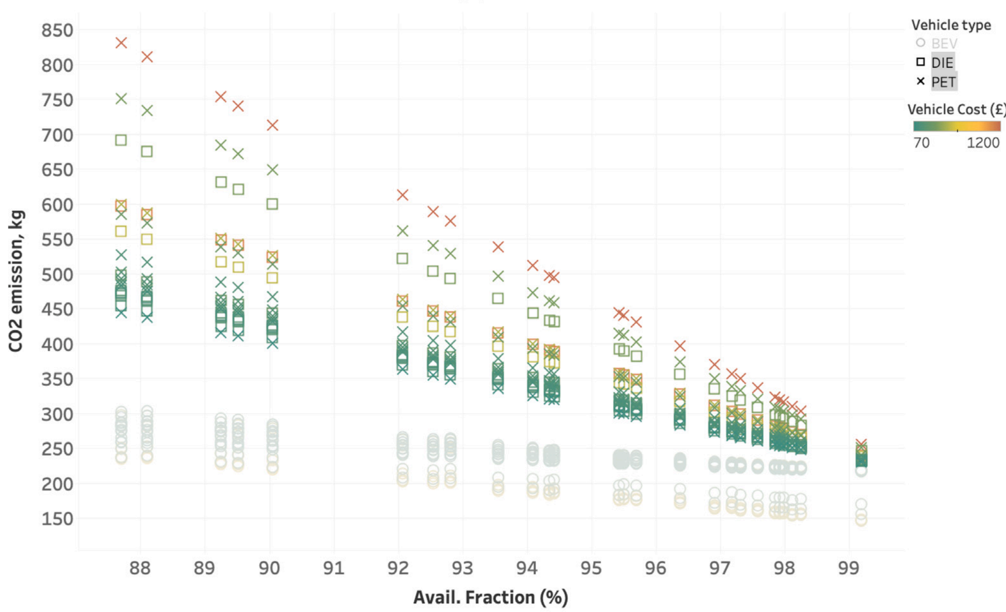
Although it has been previously mentioned that the vehicle purchase cost contributes significantly to the total cost, it has also been observed that a range of other factors are quite important. To better understand which properties significantly contribute to costs (total and electricity) and/or CO_2 emissions, a dominance analysis (Budescu, 1993; Azen and Budescu, 2003) was carried out on the results obtained from the solution of the optimisation model for the case study analysed. Dominance analysis seeks to find the relative importance of predictor (independent) variables by examining their additional contributions (in our case, their incremental R^2) in all possible subset regression models for specified target (dependent) variables (Azen and Budescu, 2003). BEV properties including the vehicle capital cost, its maintenance cost, battery capacity, power and efficiency (km/kWh); the AF of the BEV as well as the size of the PV cell installed were analysed to determine their relative importance with respect to the total cost, electricity cost or CO_2 results obtained from the optimisation models. For the total cost and electricity cost, the minimum cost optimisation model results were used, and the minimum CO_2 optimisation model results were used for CO_2 dominance analysis.

Fig. 13 shows the relative importance (%) results from the dominance analysis differentiated by target variables (total cost, electricity cost and CO_2) and the 2WP feature. The data was split based on the 2WP feature owing to the marked differences in the results observed in previous sections. A clear observance across-the-board is the difference in the order of relative importance of predictor variables for each target variable. As expected, the vehicle capital cost was the most important variable when considering total costs for all BEVs. The AF, which directly translates to how frequently the vehicle is driven, is not amongst the top 5 variables and points to the fact that the BEV's properties — battery power, capacity and travel efficiency, are much more important when bearing total costs in mind. As users may be constrained to a choice of vehicles (and thus its capital and maintenance cost) owing to a number of social factors (Lee and Brown, 2021a), results show that the BEV's battery capacity and travel efficiency are the next most important factors to consider when such vehicle has the 2WP feature. For those without 2WP, battery power dominates both its capacity and efficiency.

For the electricity cost, the AF and size of the installed PV cell were the most important considerations for all BEVs though at varying degrees. The AF is much more important for the BEV with 2WP, over PV size, as it influences its energy demand and availability for charge/discharge events. As observed in previous sections, the vehicle costs (capital and maintenance) had little or no influence on the electricity cost. In all cases, it was more important to consider the BEV's travel efficiency (km/kWh) and its capacity (BEVs with 2WP) than its capital/maintenance cost. A similar trend is observed when the goal is the total CO_2 emissions rather than cost. A difference is that the BEV's travel efficiency is the third most important factor for vehicles without 2WP as it directly influences how much electricity it consumes (which may be imported from the grid leading to an increase equivalent CO_2). For BEV's with 2WP, a larger battery capacity can compensate owing to its increased ability to time-shift electricity use. Given that the AF may be somewhat fixed for a user, aside from obtaining renewable energy



(a) BEV



(b) PET & DIE

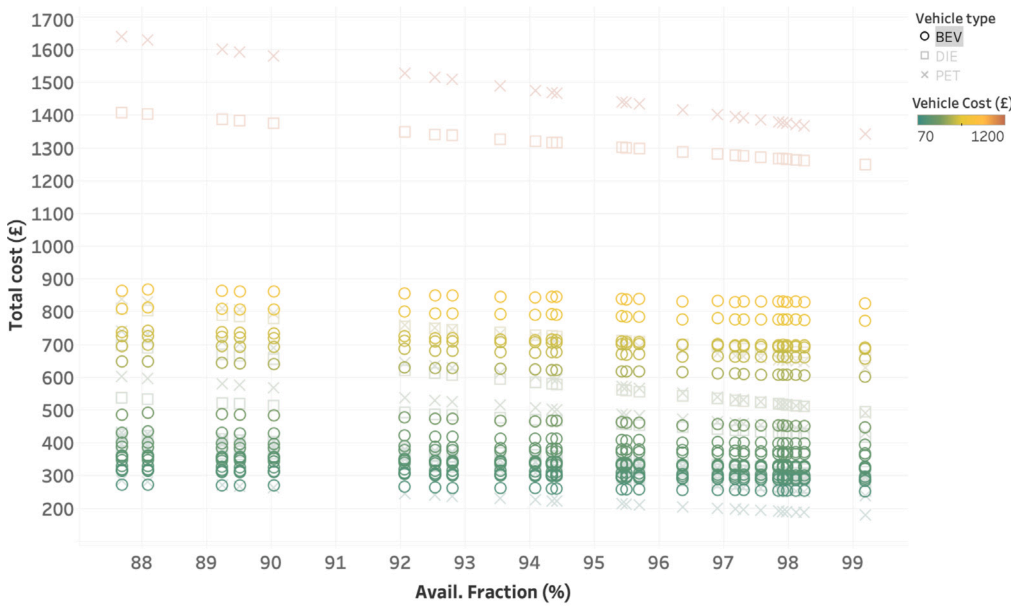
Fig. 11. Monthly CO_2 emissions vs vehicle usage; No PV (CO_2 objective).

sources, additional CO_2 benefits may be realised by first considering the BEV's battery capacity above other properties.

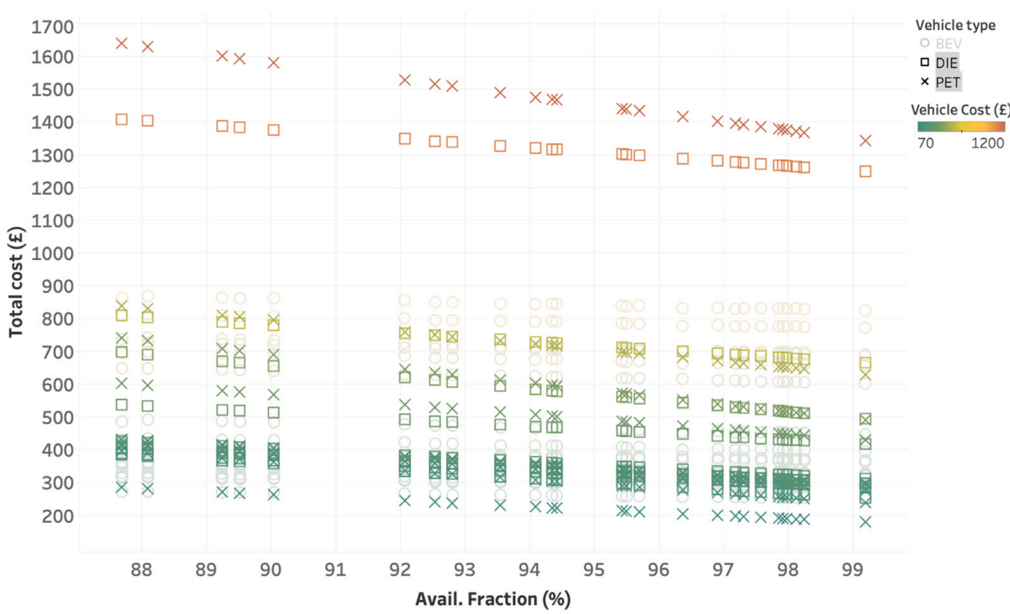
3. Conclusion and policy implications

In this work we sought to address some of the cost-related barriers to EV adoption experienced by domestic end-users. Using an optimisation model, the economic and environmental benefits for domestic EV owners were evaluated and compared with conventional non-EVs. This was carried out for a number of vehicle types with varying purchase and maintenance costs, vehicle properties such as the fuel/energy consumption rate, installed battery capacity, power, and range, all based on actual vehicles on the market. Variations in installed PV system sizes, user travel behaviour profiles, and retail electricity tariffs were also analysed.

A number of conclusions were drawn from this study. BEVs still present a cost-competitive case for vehicle owners despite having a higher up-front capital cost when compared to prevailing conventional ICE vehicles. Electricity cost savings were realised for BEVs with 2WP when compared with non-EVs for a total cost minimisation objective. Electricity costs for users of BEVs without the 2WP feature was comparable with non-EVs with a low frequency of use, but higher as the availability fraction (AF) reduced. Despite these, and even for a total cost minimisation objective, all BEVs still had a lower emission level. Furthermore, the total cost values for BEVs were similar to those for conventional ICE-type vehicles despite the latter being half the purchase price of the former, especially with higher vehicle use. BEVs were also less responsive, in terms of total cost, to changes in the degree of vehicle use than their conventional ICE counterparts. For a CO_2 emissions minimisation objective, much higher electricity costs were



(a) BEV



(b) PET & DIE

Fig. 12. Monthly total cost vs vehicle usage; No PV (CO_2 objective).

realised by BEVs with those with 2WP still achieving electricity cost savings at higher AFs. Total cost values, however, were still comparable with ICE vehicles, but much still needs to be done in terms of the affordability of EVs to ensure increased adoption by new users.

A dominance analysis was also carried out on the optimisation models results to ascertain the relative importance of specific variables in predicting the total cost, electricity cost or CO_2 emissions. For total cost predictions, aside from the obvious importance of the BEV's capital and maintenance cost, results showed that the battery power or capacity was the next most important variable to consider by a user depending on whether the vehicle has the 2WP feature or not. In all cases, the AF of the BEV was of little significance. Electricity cost and CO_2 emission predictions showed similar trends with the AF and size of the installed PV dominating all other variables in that order, but in varying degrees depending on the 2WP feature availability.

These results further confirm that the electrification of transport is a right step towards achieving net-zero goals. However, policies that incentivise EV purchase, e.g., capital cost subsidies, will encourage EV adoption by domestic end-users. It is also widely cited that lack of knowledge is a significant barrier to energy efficiency (Chen et al., 2022), and by implication costs. In order to help people make more efficient and economic decisions related to EV use and adoption, education relating to efficient EV charge scheduling as obtainable from our proposed optimisation model is important. User-friendly mobile tools with integrated optimisation models can be applied to products on market to allow users realise cost savings unique to their lifestyle. The

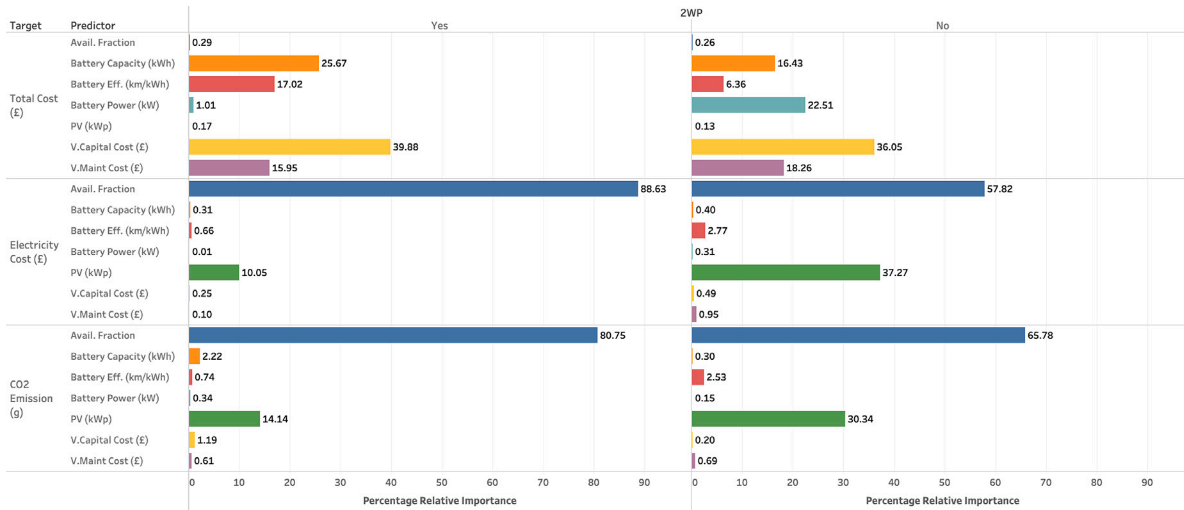


Fig. 13. BEV: Relative importance results for different predictor variables & target variables.

results also show the importance EV battery power and capacity has on cost calculations. Thus, the encouragement (e.g., through funding) of technology innovations focused on the enhancement of these battery properties for EVs will be a step in the right direction.

Additional areas need to be further explored. This work was based on a fixed location in the UK and studies have shown that location has an impact on the viability of stationary energy storage devices, and the driving patterns of users. Locational difference may also be taken into consideration not just for storage considerations but for domestic EV users as well. Further work on the impact of these findings on how domestic user may act is also important — charging patterns, driving patterns, and ultimately EV adoption.

CRediT authorship contribution statement

Jude O. Ejeh: Conceptualization, Methodology, Software, Formal analysis, Visualization, Writing – original draft. **Diarmid Roberts:** Visualization, Writing – review & editing. **Solomon F. Brown:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix. Mathematical formulation

Nomenclature

Indices

e	electricity tariff
$\hat{k}$	piecewise linearisation points for $\hat{C}_{st}$ variables
s	vehicle
$t.t'$	time/period

Set

S	set of vehicles
$\hat{S}$	subset of electric vehicles
T	set of time/period over scheduling horizon

Parameters

δ_t^V	total distance travel by vehicle at time t in Miles
Δ	time step expressed as a fraction of an hour
η_s^C	charging efficiency of energy storage device in vehicle s
η_s^D	discharging efficiency of energy storage device in vehicle s
λ_s	0,1 indicator if vehicle s can participate in V2H services ie. has the 2WP feature;
ν_{st}	availability of vehicle s at time t; {0,1}
ρ_s^C	purchase cost for vehicle s in £/year
ρ_{et}^E	electricity sell price for tariff e at time t in £/kWh
ρ_s^F	fuel cost for vehicle s in £/MILE
ρ_{et}^I	electricity purchase price for tariff e at time t in £/kWh
ρ_s^M	maintenance cost for vehicle s in £/year
ρ^S	PV purchase cost in £/year
Υ_t^G	CO_2 intensity of imported power at time t
Υ_s^V	CO_2 emitted by vehicle s per MILE of travel
$\overline{C}_s$	capacity of energy storage device in vehicle s in kWh
D_t^B	building/household load/energy demand at time t in kWh

D^V_{st}	energy consumption of electric vehicle s during travel at time t in kWh
G_t	solar generation of installed PV systems at time t
M	a big number
P^{max}_s	rated power output of energy storage device in vehicle s
SOC^0_s	initial state of charge of energy storage device in vehicle s in %
SOC^{max}_s	maximum allowable state of charge of energy storage device in vehicle s in %
SOC^{min}_s	minimum allowable state of charge of energy storage device in vehicle s in %
Binary variables	
B^C_{st}	1 if energy storage device in vehicle s is charging at time t at home; 0 otherwise
B^D_{st}	1 if energy storage device in vehicle s is discharging at time t at home; 0 otherwise
B^E_e	1 if electricity tariff e is selected; 0 otherwise
B^N_t	1 if power is exported at time t; 0 otherwise
B^S_s	1 if vehicle s is selected for use; 0 otherwise
Continuous variables	
ξ_{st}	slack variable for vehicle s at time t
$\mathcal{T}^C_s$	total capital cost over considered time horizon for vehicle s
$\mathcal{T}^M_s$	total maintenance cost over considered time horizon for vehicle s
Y_s	total equivalent CO_2 emitted at time t
$\hat{C}_{st}$	fraction of total battery capacity degraded in vehicle s at time t
D_{st}	net energy demand of energy storage device in vehicle s at time t
D^+_{st}	energy demand of energy storage device in vehicle s at time t whilst charging
D^-_{st}	energy output of energy storage device in vehicle s at time t whilst discharging
L_t	net load of energy system at time t
L^+_t, L^-_t	load of energy system at time t in deficit or surplus states respectively
P_t	net load of energy system at time t
P^I_t, P^E_t	power imported, exported by system at time t respectively
$\hat{P}^I_{et}, \hat{P}^E_{et}$	power imported, exported under tariff e by system at time t respectively
P^{s+}_{st}, P^{s-}_{st}	power demand/output of energy storage device in vehicle s at time t respectively
SOC_{st}	state of charge of energy storage device s at time t in kWh

The proposed techno-economic-environmental mathematical model used for this study is described below. It solves the optimisation problem posed as follows:

Given:

- a set of vehicles with known type — BEV, PET, or DIE, property — fuel/energy consumption, CO_2 equivalent emission (tailpipe CO_2), and two-way power feature, and cost information — purchase cost, maintenance cost;
- a set of retail electricity tariffs;
- the electricity load profile and travel behaviour of a user over a candidate time period;
- an installed photovoltaic (PV) cell peak power rating, output profile and purchase cost over a candidate time period;
- the properties of the battery within a vehicle – capacity, power, minimum/maximum SOC, round-trip efficiency, type – if an EV;
- the CO_2 equivalent emission for power imported from the grid;

determine:

- the optimal choice of vehicle;
- the optimal charging profile of the vehicle if an EV, and its dispatch profile where the two-way power feature is present;

so as to: minimise:

- the total cost of electricity purchased from the grid, purchase and maintenance of the vehicle, and purchase of the PV cell when installed; OR
- the total CO_2 emission from electricity used from the grid and vehicle during travel.

The following assumptions hold in the proposed model:

- internal modes of battery charging within BEVs e.g. regenerative braking are not considered;
- only BEV can be charged through an external power source, and may have bi-directional power (2WP) feature if specified by the manufacturer;
- for non-EVs, the SOC, battery capacity, power and round-trip efficiency are assigned a zero value;
- all EVs with installed batteries are of the Lithium ion (Li-ion) type and calendar degradation is not considered;
- all EVs charge at home only. When trips, in accordance with the user travel behaviour, require energy greater than the EV's capacity, the vehicle is assumed to return home at its minimum allowable charge level;
- the lifetime of all vehicles considered is 12 years. This falls within the year range reported by Department for Transport (2020a) having the highest percentage of registered vehicles in the UK over the past 6 years;

Eq. (A.1) defines the bounds on the capacity for the battery within the vehicle. For the first time period, an initial SOC, SOC^0_s (Eq. (A.2)), is assumed for all EVs ($s \in \hat{S}$) with subsequent time periods taking reference from the previous time's battery level (Eq. (A.3)).

$$SOC^{min}_s \overline{C}_s B^S_s \leq SOC_{st} \leq SOC^{max}_s \overline{C}_s B^S_s \qquad \forall\, s,t \tag{A.1}$$

$$SOC_{st} = SOC^0_s + \Delta \cdot (\eta^C_s P^{s+}_{st} - \frac{P^{s-}_{st}}{\eta^D_s}) \qquad \forall\, s \in \hat{S}, t = 1 \tag{A.2}$$

$$SOC_{st} = SOC_{s,t-1} + \Delta \cdot (\eta^C_s P^{s+}_{st} - \frac{P^{s-}_{st}}{\eta^D_s}) - D^V_{st} B^S_s + \xi_{st} \qquad \forall\, s \in \hat{S}, t \tag{A.3}$$

Where D^V_{st} is the energy consumption of the EV s during travel at time t in kWh. An additional positive variable ξ_{st} is included in Eq. (A.3) to prevent model infeasibilities should the battery capacity be insufficient for a particular trip's range. The variable is then included in a penalty term in the objective function. Where this occurs, the EV then returns home at the end of its trip at its minimum allowable SOC.

The net power, P_t, required by the home is given by Eq. (A.4) as the difference between the power imported, P^I_t, and exported, P^E_t, at a particular time period.

$$P_t = P^I_t - P^E_t \qquad \forall\, t \tag{A.4}$$

The total power imported and exported is given as the sum of the power demanded locally and the net power supplied by the vehicle (if an EV), less the amount supplied by the installed PV cell.

$$P^I_t - P^E_t = \frac{D^B_t}{\Delta} + \sum_s (P^{s+}_{st} - P^{s-}_{st}) - \frac{G_t}{\Delta} \qquad \forall\, t \tag{A.5}$$

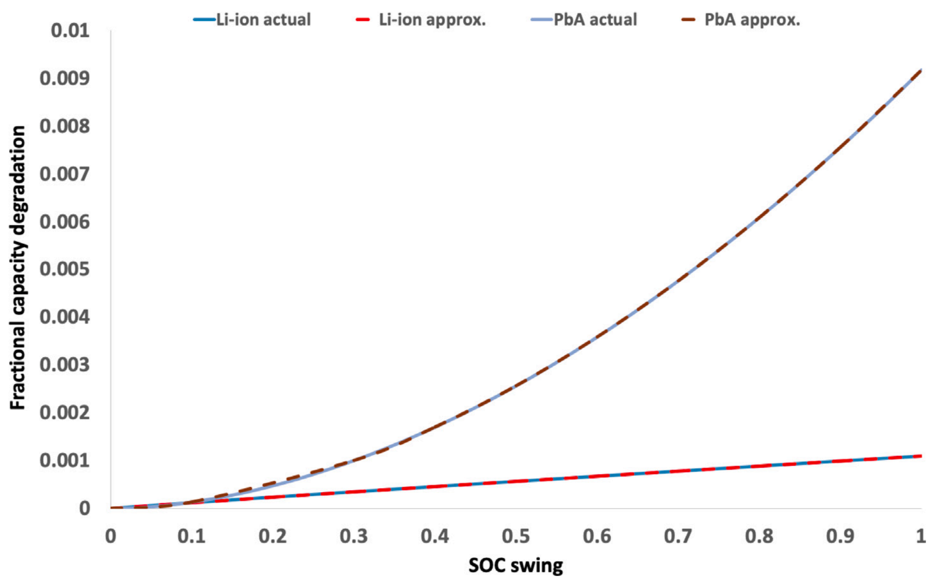

Fig. A.14. Fractional capacity degradation vs SOC swing for Li-ion & PbA batteries.

As power imports and exports cannot occur simultaneously, Eqs. (A.6) and (A.7) are introduced.

$$P^I_t \leq M \cdot (1 - B^N_t) \qquad \forall\, t \tag{A.6}$$

$$P^E_t \leq M \cdot B^N_t \qquad \forall\, t \tag{A.7}$$

Where M is a big number. Given a set of vehicles, for the purpose of this work, only one vehicle may be selected (Eq. (A.8)):

$$\sum_s B^S_s = 1 \tag{A.8}$$

$$P^{s+}_{st} \leq P^{max}_s B^S_s \qquad \forall\, s, t \tag{A.9}$$

$$P^{s-}_{st} \leq P^{max}_s v_{st} B^S_s \qquad \forall\, s, t \tag{A.10}$$

When a vehicle is selected, the charging/discharging power must be less than its rated power (Eqs. (A.9) and (A.10)).

Binary variables B^C_t and B^D_t are introduced denoting time periods during which the battery within a vehicle is charging and discharging respectively (Eqs. (A.11) and (A.12)). The battery may only charge/discharge from/to the home when they are located at home (Eq. (A.13)), and may only discharge to the home if they are selected and have the 2WP feature (Eq. (A.14)).

$$\sum_s P^{s+}_{st} \leq M \cdot B^C_t \qquad \forall\, t \tag{A.11}$$

$$\sum_s P^{s-}_{st} \leq M \cdot B^D_t \qquad \forall\, t \tag{A.12}$$

$$B^C_t + B^D_t \leq v_{st} \qquad \forall\, t \tag{A.13}$$

$$B^D_t \leq \lambda_s B^S_s \qquad \forall\, t \tag{A.14}$$

The total CO_2 emitted at time t is given by Eq. (A.15) as the sum of the CO_2 equivalent of the imported power (P^I_t) and that emitted from driving the selected vehicle over a distance, δ^V_t, based on its stated ratings.

$$Y_t = \Delta \cdot Y^G_t P^I_t + \sum_{s\in\hat{S}} \delta^V_t Y^V_s B^S_s \qquad \forall\, t \tag{A.15}$$

The capital cost over the considered time horizon is evaluated by Eq. (A.16) as the sum of the purchase cost of the selected vehicle, installed PV cell, and the fuel cost during travel. The maintenance cost is also evaluated using Eq. (A.17)

$$\mathcal{T}^C_s = \left(\Delta|T| \cdot \frac{\rho^C_s + \rho^S}{24 * 365} + \sum_s (\rho^F_s \delta^V_t)\right) B^S_s \qquad \forall\, s \tag{A.16}$$

$$\mathcal{T}^M_s = \Delta|T| \cdot \frac{\rho^M_s B^S_s}{24 * 365} \qquad \forall\, s \tag{A.17}$$

Given a set of electricity tariffs, only one may be selected (Eq. (A.18)). To avoid non-linear terms resulting from evaluating the electricity import/export costs for a selected tariff, $\hat{P}^I_{et}$ and $\hat{P}^E_{et}$ variables are introduced representing the power imported/exported for each tariff. Both variables take non-zero values only if a tariff is selected (Eqs. (A.19) and (A.20))

$$\sum_e B^E_e = 1 \tag{A.18}$$

$$\hat{P}^I_{et} \geq P^I_t - M \cdot (1 - B^E_e) \qquad \forall\, e, t \tag{A.19}$$

$$\hat{P}^E_{et} \leq P^E_t - M \cdot B^E_e \qquad \forall\, e, t \tag{A.20}$$

Battery degradation is modelled according to the power law relationship given by Ciez and Whitacre (2016). Eq. (A.21) gives the expression for Li-ion and PbA batteries, where $\hat{C}_t$ represents the fraction of the total capacity degraded at time t by reason of the SOC swing (SOC^{sw}_t) from battery actions in the previous time periods. The SOC swing is determined as the actual depth of discharge over the past 24 h of battery operation.

$$\hat{C}_{st} = \begin{cases} \left(\dfrac{SOC^{sw}_{st}}{1307.4}\right)^{0.95}, & type(s) \in \{\text{Li-ion}\} \\ \left(\dfrac{SOC^{sw}_{st}}{12.838}\right)^{1.838}, & type(s) \in \{\text{PbA}\} \end{cases} \qquad \forall\, t \tag{A.21}$$

Eq. (A.21) is a non-linear expression that is linearised using a piece-wise linear approximation as follows (D'Ambrosio et al., 2010). First, two positive variables SOC^{sl}_t and SOC^{sh}_t are introduced to represent the minimum and maximum SOC of the battery at 24-hour intervals respectively. These are evaluated using Eqs. (A.22) and (A.23):

$$SOC^{sl}_{st} \leq \frac{SOC_{s,t-t'}}{\bar{C}_s} \qquad \forall\, s \in \hat{S},\ t\%(\frac{24}{\Delta}) = 0,\ t' \leq (\frac{24}{\Delta}) \tag{A.22}$$

$$SOC^{sh}_{st} \geq \frac{SOC_{s,t-t'}}{\bar{C}_s} \qquad \forall\, s \in \hat{S},\ t\%(\frac{24}{\Delta}) = 0,\ t' \leq (\frac{24}{\Delta}) \tag{A.23}$$

The SOC swing is then given by Eq. (A.24).

$$SOC^{sw}_{st} = SOC^{sh}_{st} - SOC^{sl}_{st} \qquad \forall\, s \in \hat{S},\ t \tag{A.24}$$

The fraction of the total capacity degraded at time t, $\hat{C}_{st}$, is then evaluated as follows. 11 equidistant sample points, $\hat{k}$ are taken for

SOC^{sw}_{st} between 0 and 1 ($SOC^{sw'}_{st\hat{k}}$) and the corresponding values of $\hat{C}_{st}$ ($\hat{C}'_{st\hat{k}}$) calculated. A special ordered set of type 2 (SOS2) variable (ϕ_{st}) is introduced and Eq. (A.21) re-written as:

$$\hat{C}_{st} = \sum_{\hat{k}} \hat{C}'_{st\hat{k}} \phi_{st} \qquad \forall\, s \in \hat{S},\, t \tag{A.25}$$

$$SOC^{sw}_{st} = \sum_{\hat{k}} SOC^{sw'}_{st\hat{k}} \phi_{st} \qquad \forall\, s \in \hat{S},\, t \tag{A.26}$$

Fig. A.14 shows a good fit of the actual vs piecewise linear approximation for the SOC swing for both Li-ion and PbA batteries. The maximum SOC of the battery is then corrected for degradations owing to use with Eq. (A.27).

$$SOC_{st} \leq (SOC^{max}_{s} B^{S}_{s} - \hat{C}'_{st})\overline{C}_{s} \qquad \forall\, s \in \hat{S}, t \tag{A.27}$$

The scheduling model cost-minimisation objective function is defined according to Eq. (A.28). It minimises the sum of the electricity import and export cost, vehicle purchase and maintenance cost, and the purchase cost of the PV system.

$$min \quad \sum_{e,t} \Delta\left(\rho^{I}_{t} \cdot \hat{P}^{I}_{et} - \rho^{E}_{t} \cdot \hat{P}^{E}_{et}\right) + \sum_{s}\left(\mathcal{T}^{C}_{s} + \mathcal{T}^{M}_{s}\right) + \sum_{s,t} M \cdot \xi_{st} \tag{A.28}$$

subject to Eqs. (A.1)–(A.20), (A.22)–(A.27).

Where the end-user's concerns are less about cost and more about emissions reduction, a CO_2 minimisation objective (Eq. (A.29)) can be adopted.

$$min \quad \sum_{s,t} Y_{t} + M \cdot \xi_{st} \tag{A.29}$$

subject to Eqs. (A.1)–(A.20), (A.22)–(A.27).

When each of the models are applied to non-EVs ($s \notin \hat{S}$), the models then solve a minimisation problem for a household without energy storage.

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