Plug and play: the impact of plug-in frequency on the potential of vehicle to grid to support transport and electricity system decarbonisation

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Abstract

Vehicle-to-grid (V2G) from electric vehicles (EVs) represents an opportunity to provide transitioning electricity systems with battery storage as they face increasing shares of variable renewable generation. However, whilst the availability of V2G as dispatchable storage depends on the travel and charging habits of drivers, there is scarce experience of managing portfolios of EVs in this way. This paper investigates the impact of plug-in frequency – given real-life travel data – on the potential of V2G to reduce i) consumer bills and ii) carbon emissions of charging. In doing so, we investigate the extent to which consumers are incentivised to participate in V2G, how this might change based on different charging behaviours and what the implications are for V2G as a storage asset. Two models of plug-in behaviour are input into a time-coupled optimisation that schedules EV (dis)charging to minimise the net cost of an EV's required energy gain within network constraints, simulating how V2G could be dispatched by a 'load controller' in a liberalised electricity market. The cost minimisation is based on the Octopus *Agile* V2G tariff in January 2021, which is matched to GB grid carbon intensity data from National Grid ESO for the same period. It was found that, on the basis of the time range studied, V2G can reduce the average price paid for EV-charging electricity by 30-68% versus a flat tariff – with the lower end of that range representing a case where consumers only plug in when they 'need' to, and the higher end representing the case where consumers plug in whenever their cars are at home. It was also found that due to the positive correlation between price and carbon, optimising for price also resulted in

reductions in carbon intensity of the EV-charging electricity by 8-12% compared to uncontrolled charging, with the range representing the same cases as before. Taking into account a review of battery degradation costs from V2G, using an EV's battery in this manner only makes financial sense to the owner if they maximise their plug-in frequency; this, alongside the increased savings, should provide an incentive to owners to plug in as much as possible – thereby maximising storage resource for a low carbon electricity system.

Keywords: Vehicle to grid, Electric vehicles, Bidirectional charging, Smart charging, Optimisation

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Nomenclature

Sets

$\mathcal{B}$	Buses, indexed by b
$\mathcal{D}$	Domestic loads, indexed by d
$\mathcal{E}$	Electric vehicle charging events, indexed by e
$\mathcal{G}$	Grid supply points, indexed by g
$\mathcal{L}$	Lines, indexed by l
$\mathcal{T}$	Time horizon comprised of ten-minutely timesteps, indexed by t

Parameters

B_l	Susceptance of line l
$\mathrm{E}_e^{\mathrm{max}}$	Battery capacity in EV for charge event e
$\mathrm{E}_e^{\mathrm{start}}$	Energy storage content of EV at start of charge event e
$\mathrm{E}_e^{\mathrm{end}}$	Energy storage content of EV at end of charge event e
$\mathrm{P}_{d,t}^{\mathrm{D}}$	Active power demand from domestic load d in time period $[t, t+1]$
$\mathrm{P}_{e,t}^{\mathrm{E}}$	Active power demand from charge event e in time period $[t, t+1]$
$\mathrm{P}_e^{\mathrm{max}}$	Max. charging power for EV in charge event e
$\mathrm{S}_l^{\mathrm{max}}$	Active power capacity of a line l

$\mathrm{t}_e^{\mathrm{in}}$	Plug-in time of EV for charge event e
$\mathrm{t}_e^{\mathrm{out}}$	Plug-out time of EV for charge event e
Δt	Difference between adjacent timesteps $[t, t+1]$
η	One-way charger efficiency

Variables

$c_t^{\mathrm{CO_2}}$	Carbon intensity of grid electricity at timestep t
c_t^{imp}	Export tariff at timestep t
c_t^{exp}	Import tariff at timestep t
$E_{e,t}$	Energy storage content of EV in charge event e at timestep t
$p_{d,t}^{\mathrm{D}}$	Active power delivered to domestic demand d during time period $[t, t+1]$
$p_{e,t}^{\mathrm{imp}}$	Active power imported by an EV in charge event e during time period $[t, t+1]$
$p_{e,t}^{\mathrm{exp}}$	Active power exported by an EV in charge event e during time period $[t, t+1]$
$p_{g,t}^{\mathrm{G}}$	Active power from grid supply point g during time period $[t, t+1]$
$p_{l,t}^{\mathrm{L}}$	Active power flow on line l during time period $[t, t+1]$
$\sigma_{e,t}$	State of charge (per unit) of EV in charge event e at timestep t
$\delta_{b,t}$	Voltage angle at bus b during time period $[t, t+1]$
γ_e	SoC at which the charging profile transitions from the constant current to the constant voltage region in charge event e

Abbreviations

CC-CV	Constant current-constant voltage
CCGT	Combined cycle gas turbine
CDF	Cumulative distribution function
ESO	Electricity system operator
EV	Electric vehicle
GB	Great Britain (referring to the largest island of the UK)
ICV	Internal combustion vehicle
NTS	National Travel Survey
SoC	State of charge (of an EV's battery)
V2G	Vehicle to grid

1. Introduction

The UK is one of an expanding set of major economies that has committed to end the sale of internal combustion vehicles (ICVs) – in this case by 2030/2035[1] at the time of writing [1] – as part of its legally-binding commitment to reach Net Zero greenhouse gas emissions by 2050 [2]. Even if private car ownership and use in the UK reduces as per wider decarbonisation strategies [3], the market dominance of battery electric vehicles (EVs) over other low carbon powertrains [4] means that it is likely that tens of millions of EVs will be bought in the UK in the next two decades.

Bi-directional charging, or *vehicle to grid* (V2G), represents a technological opportunity for decarbonisation at the intersection of the transport and electricity sectors. Firstly, by providing a revenue stream for EV (or charge point) owners, V2G can encourage EV uptake (or charge point installation) and hasten the transition from ICVs [5]. Secondly, V2G enables the provision of fast-responding electricity storage from vehicles that are sat in

[1] 2030 is the current phase-out date for purely internal combustion powered vehicles; the sale of plug-in hybrids is due to be banned in 2035.

peoples' homes – in short, there is the potential for a significant proportion of the UK's required electricity storage[2] as it adopts increasing levels of variable renewables to be met by the control of EV batteries.

Unlike stationary battery storage, the availability of V2G depends on how often the EV is plugged in and what the travel requirements of the EV are. Emerging business models for V2G are centred on a 'load controller' (an entity such as an aggregator or supplier) sending requests and incentives to a charge point, facilitating power flow to and from the vehicle's battery in line with consumer wishes and offering that flexibility into a series of markets from the balancing mechanism to dynamic containment [8]. Due to the infancy of V2G there is very little experience of managing portfolios of EV batteries as dispatchable battery storage, and so the level of resource at an aggregated level is difficult to estimate.

Whereas V2G depends on customers plugging in their vehicles as much as possible, it has been shown that drivers tend to plug their vehicles in less often than every time they arrive home, particularly for vehicles with larger batteries – in the 2016-2019 trial *Electric Nation*, drivers of larger battery (40-60 kWh) EVs were found to plug in half as frequently (2.2 times per week vs. 4.4 times per week, on average) as drivers of smaller battery (10-25 kWh) EVs [9].

This paper presents a study of the impact of plug-in frequency on the potential of V2G to reduce i) consumer bills and ii) carbon intensity of charging. Implicit in V2G doing these things is the provision of much-needed flexibility in demand, reducing the need to reinforce distribution networks and therefore alleviating the difficulty of recovering investments in networks with low load factors and peaky demands.

Two models of plug-in behaviour are presented based on a charging schedule heuristic developed in previous work [10]; a 'minimal' charging model in

[2]In their 2019-published Net Zero pathway *Innovating to Net Zero* [6], the Energy Systems Catapult estimates that the UK would need 29-35 GWh of electricity storage for a Net Zero-compliant generation mix to meet demand and maintain grid stability. If there are 20-30 million EVs on the UK's roads by 2050 as in National Grid Electricity System Operator (ESO)'s *Future Energy Scenarios 2020* [7], and the average EV battery capacity is 40-60 kWh, then there would be 800-1800 GWh of battery storage distributed amongst the UK's private cars. Even for low rates of V2G uptake, there is clearly potential for in-vehicle battery storage to support the integration of variable renewable generation in the electricity system.

which drivers schedule their charge events with the goal of minimising the number of plug-ins (in the aim of maximising the 'convenience' of EV use), and a 'routine' charging model in which drivers always plug in upon arrival at home, regardless of their battery's state of charge (SoC) or upcoming journey requirements. The charging models generate week-long charging schedules that satisfy the energy requirements for week-long travel diaries – in this case from the UK National Travel Survey (NTS). The charging schedules output from these models and the travel data are used with a new V2G formulation that seeks to minimise cost according to two variable tariffs, an import (buy) price and an export (sell) price – taken from the Octopus *Agile* V2G tariff as available at [11]. Due to the positive correlation between the price of electricity and its carbon intensity (as explored in section 4.1), the study also quantifies the potential reduction in carbon intensity from V2G when optimising on cost. This is done by linking the tariff data with carbon intensity data from National Grid ESO [12] for the same time period in January 2021.

The rest of the paper is organised as follows: section 2 provides a literature review on the state of the art of V2G modelling and trials; section 3 describes the methodologies used in this study; section 4 presents the results, which are discussed in section 5; section 6 presents conclusions and suggests pieces of future work based on this paper.

2. Previous work on *vehicle to grid*

2.1. Establishing value in vehicle to grid

Put simply, the presence of value in V2G depends on the sum total of revenues compared to any costs. To this end, there have been many works in the literature on establishing different revenue streams for EVs participating in V2G, looking to maximise the revenue for individual vehicle owners or fleet operators. An investigation into different business cases available to a fleet operator through participating in V2G is presented in [13], in which it was found that participation in the balancing mechanism offers the most reward compared to other accessible parts of the electricity market in 2017 when the paper was published. In [14], the authors analyse the potential for EV fleet aggregators' participation in frequency support in both Denmark and Japan, based on the export price per unit power within the frequency response markets – establishing that profitability is only achieved when V2G is done on an 'industrial' scale. A rule-based optimisation for V2G is presented in [15], where each EV in a set seeks to minimise its cost based on GB wholesale electricity prices – in which the process is found to be economically feasible based on the changes in wholesale electricity prices. Analysis of the potential for V2G to participate in a set of regulating power services is presented in [16], where the results indicate that while V2G is profitable in Germany, it is not in Sweden. Optimisation of V2G within a UK science park (with adjacent behind-the-meter demand, solar generation and a grid connection) is presented in [17], in which it is found that net present values of £8,400 per vehicle are achievable over a 10-year time frame.

There have also been works on the system-wide benefits from V2G, on the premise that the value of V2G should be unlocked for operators of electricity systems, generators and/or distribution networks. In [18], the authors present analysis into the potential reduction in curtailment of wind generation in Denmark by a 'nationwide battery' approach where half a million EVs are aggregated into one virtual power plant – concluding that curtailment can be reduced by up to 21% over a year from using the aggregated EV fleet in V2G. In [19], the extent to which V2G can reduce peak demand – and therefore distribution network losses and the need for reinforcements – is analysed across exemplar UK and Texas networks: it was found that peak demand could be reduced by up to 35% and 20% in the British and Texan networks respectively. In [20], the authors evaluate the potential for V2G to maximise the self-consumption of solar generation within an export-constrained network in Italy.

2.2. Plug-in behaviour modelling

The biggest difference between stationary battery storage and using V2G as battery storage is the variable availability of the latter. While the data governing the availability of the vehicles in [13–20] varies between travel data or simpler, fixed assumptions (such as in [14], where scenarios are used to represent the availability of EVs – for example, all vehicles being assumed connected between 17:15 and 06:00), all of them are predicated on the assumption that if a vehicle can charge when it arrives at a charger, it will do so regardless of its SoC or future travel demand.

Conversely, it has been shown that EV charging behaviour is diverse across its users [21, 22] and it is apparent that EVs are plugged in less often than every time they arrive home – as already stated, drivers in the 2016-2019 trial *Electric Nation* [9] plugged in half as frequently if they had access to a vehicle with a larger battery capacity.

There have been works to model EV charging behaviour and examine the resulting impact on networks. In [23], the authors propose a probabilistic model that combines NTS trip data with charging data from the *My Electric Avenue* EV trial and, using an aggregation at a scale of 50 vehicles, assign peak demand and energy demand values to 50-household networks across GB based on the distribution of car ownership across the country. Studies in [24–26] present probabilistic models based on EV trial data alone and apply the resulting charge events to models of real distribution networks; [27–29] use travel data to simulate charge events on distribution network models, based on algorithms that derive credible charge events from trip data.

2.3. Research gaps and contributions of this paper

While there have been a significant number of works in evaluating the value of V2G [13–20] and also a significant number of works modelling plug-in behaviour [23–29], there is not – to the authors' knowledge – anything in the literature that seeks to quantify the effect of plug-in behaviour on the value of V2G.

Nor has any literature been found that explicitly examines the potential for V2G using real-world tariffs, as the Octopus *Agile* tariff data is used in this paper. While many of the V2G studies discussed use price profiles to assess value in V2G, none of them used tariff data that would be directly available to a domestic consumer. This is an important gap, as the savings made by a household on charging their EV's battery is an important motivator in encouraging V2G uptake (and therefore higher levels of flexible resource for a low carbon electricity system).

This paper represents a novel contribution in linking vehicle trip data to potential V2G resource – and how it affects consumer bills and the carbon intensity of the electricity used to charge the EVs – for different modes of charging plug-in frequency.

3. Method

3.1. Summary and Previous Work

This paper builds on a heuristic model to generate credible charging schedules given travel data originally presented in [10] and a time-coupled linearised optimal power flow formulation for a smart (one-way) charging study originally presented in [30]. In the interest of conciseness, the methodologies used to derive i) charging schedules given travel data based on EV fleets instantiated in distribution networks and ii) flexible charging events (in which the time in, time out, energy required and power rating are prescribed), are only briefly described in this paper. For full details of the methods, the reader is referred to [10] and [30] where relevant in this section.

The complete set of data, models and methods in this work is shown in Figure 1 as three modules labelled 1, 2 and 3.

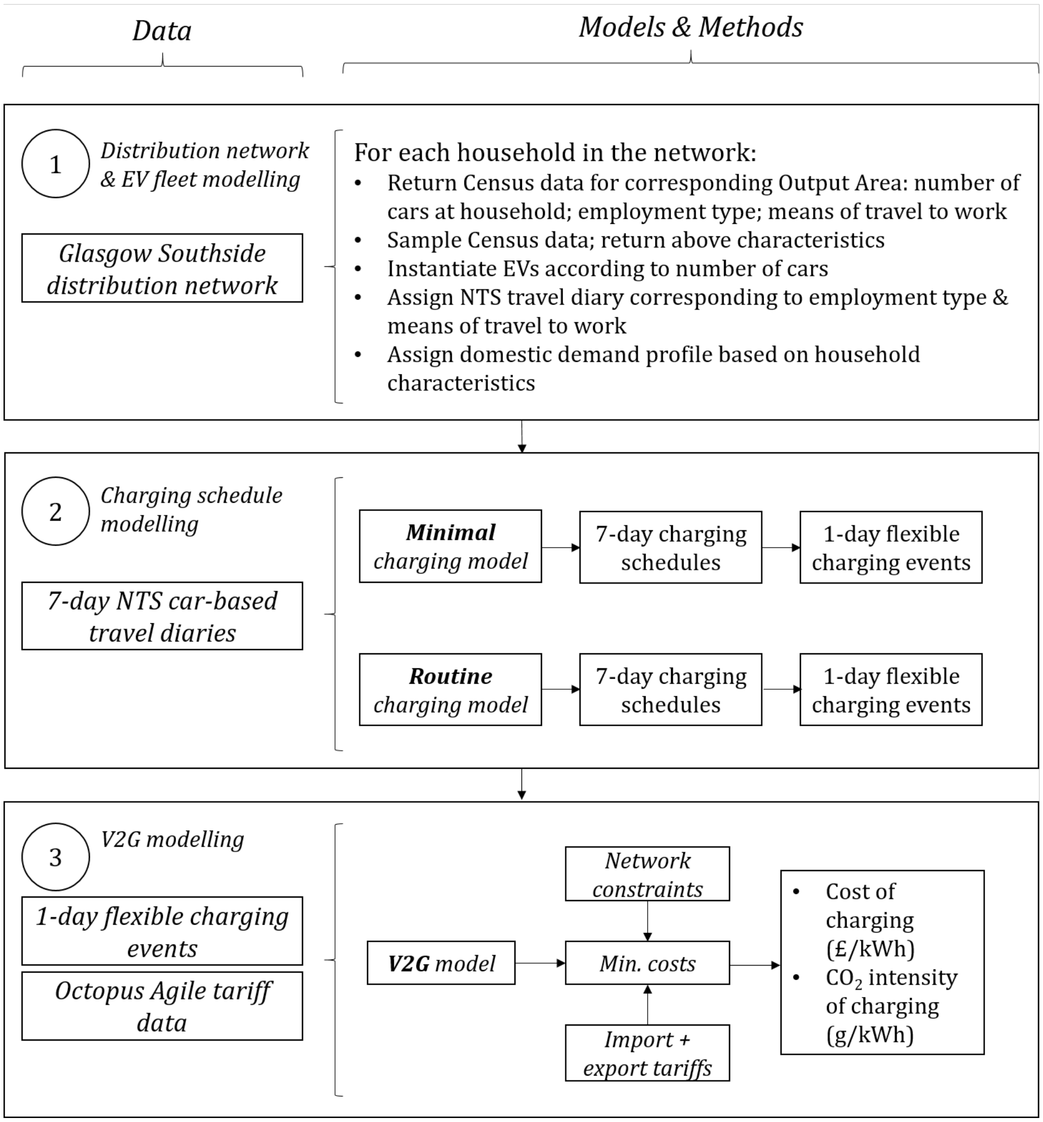

Figure 1: Data, models and methods used in this work, including those referenced in previous outputs and those new to this paper

In Figure 1, modules 1 and 2 are both described in detail in [30]. The justification for the sociotechnical approach outlined in module 1 – by which NTS diaries are disaggregated by employment and means of travel to work – is presented in [27]. The minimal charging model shown in module 2 is detailed in [10].

While this paper builds on a large foundation of previous work, key parts of modules 1 and 2 in Figure 1 are briefly summarised in sections 3.3 and 3.4 respectively, so that this paper can be read as a standalone work.

3.2. Data sources

3.2.1. UK National Travel Survey

The UK NTS is an annual survey in which around 15,000 UK residents fill out a week-long travel diary, providing details such as the mode, distance, time and duration of all trips made over a 7-day period [31]. The 7-day period recorded differs between the individuals, hence minimising any bias from seasonal variation/holidays. The resulting dataset for the years 2002-2018 as used in this study contains details of over 2 million car-based trips split between over 100,000 vehicles, which have been aligned such that they all take place from 00:00 on Monday to 23:59 on Sunday. An example NTS travel diary, showing only car-based trips, is shown in Table 1.

Table 1: Example UK NTS travel diary (car-based trips)

Trip #	**Origin**	**Destination**	**Trip Start**	**Trip End**	**Distance (miles)**
1	Home	Food shop	Tu 09:30	Tu 09:50	3
2	Food shop	Home	Tu 10:40	Tu 11:00	3
3	Home	Other escort	Tu 18:15	Tu 18:20	0.25
4	Other escort	Home	Tu 18:20	Tu 18:25	0.25
5	Home	Other escort	Tu 19:40	Tu 19:45	0.25
6	Other escort	Home	Tu 19:50	Tu 19:55	0.25
7	Home	Food shop	W 09:30	W 09:50	3
8	Food shop	Home	W 10:30	W 10:45	3
9	Home	Work	Su 07:40	Su 08:00	7
10	Work	Home	Su 17:00	Su 17:20	7

3.2.2. Octopus Agile tariff data

Octopus' *Agile* electricity tariff [32] is designed for consumers who can shift their demand in time to make use of lower wholesale prices. The tariff rate changes by the half-hour, and is communicated through the GB smart metering system. There are two tariffs as part of *Agile*: an import tariff that is limited to maximum of £0.35/kWh, but that can go negative in times of low demand and high supply from variable renewables, and an export tariff that consumers are paid per unit of electrical energy that they send to the grid – either from local solar/wind generation, or from a V2G-capable EV charge point.

Historical data for the Octopus *Agile* tariff is available from Energy-stats UK [11]. The 10-day period in this study is the 6^{th}-16^{th} January 2021 inclusive; in that period, both import and export tariffs are shown to vary significantly (Figure 2). The tariff differs according to GB region; the data shown in Figure 2 corresponds to South Scotland as to be of most relevance to the Glasgow Southside distribution network (Figure 3) from which the EV fleet is instantiated. As shown in Figure 2, the export tariff exceeds the import tariff – times during which a charge point would generate revenue by exporting to the grid – on 7 out of 10 days.

As typical of the British midwinter, the tariffs are higher than the year-round average for this tariff as demand is naturally higher than at other times of year. For the 10-day period under study, the average import tariff and export tariff values were £0.18 and £0.12 respectively. The averages of the historical data from [11] (which go back to February 2018 for the import tariff and May 2019 for the export tariff) are £0.14 for the import tariff and £0.06 for the export tariff.

3.2.3. National Grid ESO grid carbon intensity data

Grid carbon intensity is the measure of grams of CO_2 emitted per kWh of electrical energy generated. As per National Grid ESO's methodology [33], the emissions are not inclusive of life cycle emissions associated with fuel processing or installations. Therefore, low carbon sources including wind, solar and nuclear are all labelled 0 gCO_2/kWh. The carbon intensity of combined cycle gas turbines (CCGT) – the dominant fossil-based generation method in GB – is taken to be 394 gCO_2/kWh.

Half-hourly GB grid carbon intensity (gCO_2/kWh) was obtained for the same 10-day period as for the *Agile* data from National Grid ESO's carbon intensity API [12]. Figure 2 shows the variation in carbon intensity over the period; it varies from a low of 98 gCO_2/kWh at 23:30 on 10^{th} January to a high of 330 gCO_2/kWh at 06:30 on 15^{th} January. The average carbon intensity during the period was 248 gCO_2/kWh, which is 25% higher than the year-round average carbon intensity (198 gCO_2/kWh in 2019, which is the most recent value available [34]). This is also typical during the winter, during which time demand is higher and higher-carbon generation sources such as CCGT plants and sometimes coal-fired power stations are dispatched.

Figure 2: Time series of Octopus *Agile* tariff and National Grid ESO carbon intensity data, 10 days in January 2021

3.3. Distribution network and EV fleet modelling

The network model used to instantiate a fleet of EVs and to set constraints on their charging is derived from a real distribution network in the residential-dominated Southside area of Glasgow, UK. The network consists of a secondary (11/0.4 kV) substation and three 0.4 kV distribution feeders. The network serves 157 households, spread amongst 47 endpoints (i.e. there are some address points that are apartment blocks with multiple households). It is assumed that the different households are equally divided among the three phases and that those phases are balanced. Figure 3 shows a plot of the network topology with the location of the grid connection highlighted (left) and a rendered 3D image of the area in question (right) – imagery from Google Maps [35].

Figure 3: Glasgow Southside network used for instantiation of EV fleet (left) and rendered 3D image of area in question (right)

EVs are instantiated according to the method summarised in Figure 1 and described in detail in [30]. The approach is a Monte-Carlo based method, in the way that the 2011 UK Census (the most recent available) distributions relating to each household served by the network are sampled each time the model is run. The model is run 10 times to produce 10 separate fleets of EVs with a corresponding set of NTS travel diaries, linked to the employment type and means of travel to work as the individuals served by the network. Each time an EV is instantiated, its battery capacity is sampled randomly from a set of capacities found on the EV market: 24, 30, 40, 60 and 75 kWh. All EVs were assumed to have 7.4 kW charging capability, to reflect the trend towards higher power home chargers[3]. All EVs have access to parked charging at home only. For more details on the effect of changing battery size, charger power and the set of locations at which the EV can charge on the resulting plug-in frequency, the reader is referred to [27].

3.4. Modelling charging schedules from travel data

Two models are used to derive charging schedules from the NTS travel diaries (e.g. Table 1), designed to represent the spectrum of likely charging

[3]in the UK, there is generally no difference in price between 'slow' and 'fast' home chargers – e.g. the WallPod EV charger retails at £320 in the UK for either 3.7 or 7.4 kW configuration [36] – thus it is likely that 7.4 kW chargers will soon become the norm.

behaviours. These methods are described in sections 3.5-3.6.

3.5. Minimal charging model

The minimal charging model represents a scenario in which plugging in an EV is seen as an inconvenience, and therefore something to be minimised. This model uses a heuristic originally presented in [10]. In summary, the model returns the minimum number of charge events required to satisfy the energy requirements of an NTS travel diary (Table 1), choosing parked charging events first and resorting to en route charging events only when parked charging opportunities are insufficient in meeting the travel diary's energy requirement. This is done by ensuring that the vehicle's SoC is always greater than or equal to a prescribed minimum; that which would give 25 km of remaining range on a 'combined' energy consumption rate, based on how far a prudent driver would be willing to drive before charging. While the EV will minimise the time spent en route charging, gaining only enough energy it needs to arrive at the end of the trip with the minimum permitted SoC, it will seek to gain the maximum energy transaction it can from any parked charging event – subject to the charger power and a standard Lithium-ion battery charging curve [10].

A detailed explanation of how this heuristic works is given in [10]. Table 2 shows a minimal charging schedule that meets the energy requirements of the NTS travel diary shown in Table 1. The SoC with which the vehicle starts the travel diary is randomised between the prescribed minimum (i.e. to give a range of 25 km at a 'combined' consumption rate) and 100%. In this example case, it was randomised as 74%.

Table 2: Minimal charging schedule derived from NTS travel diary in Table 1 for an EV with a battery capacity of 24 kWh and a home charger rated at 3.7 kW AC

Trip #	**Charge Type**	t^{in} (**Plug-in**)	t^{out} (**Plug-out**)	E^{start} **(kWh)**	E^{end} **(kWh)**	P^{max} **(kW)**
8	home	W 10:45	Su 07:40	8.44	24	3.7

In Table 2, t^{in} and t^{out} are the plug-in and plug-out times respectively; E^{start} and E^{end} are the energy storage contents of the EV at the start and end of the charge events respectively. P^{max} is the maximum rated AC (grid-side) power the EV can be charged at.

Table 2 shows that the EV was able to charge sufficiently to meet the energy requirements of its travel diary with one parked charging event taken at home at the end of trip 8. Note that although they could have charged after trips 2, 4 and 6, the driver chose not to as they could defer their charging until later in the week, thus finishing the week's travel diary with the maximum possible SoC.

To validate that the plug-in frequency produced from the minimal charging model is representative of real-life EV driver behaviour, Figure 4 (originally presented in [30]) shows the resultant charging frequency (plug-ins per week) for sets of simulated charging schedules based on fleets of 10,000 EVs for two battery sizes, 24 kWh and 64 kWh. On the same axis is data from the *Electric Nation* EV trial [9]; note that the battery sizes used for the latter are the midpoints of the intervals reported, e.g. where the project reported that EVs with batteries of 10-25 kWh charged on average 0.63 times per day, the corresponding value used for the figure is 17.5 kWh.

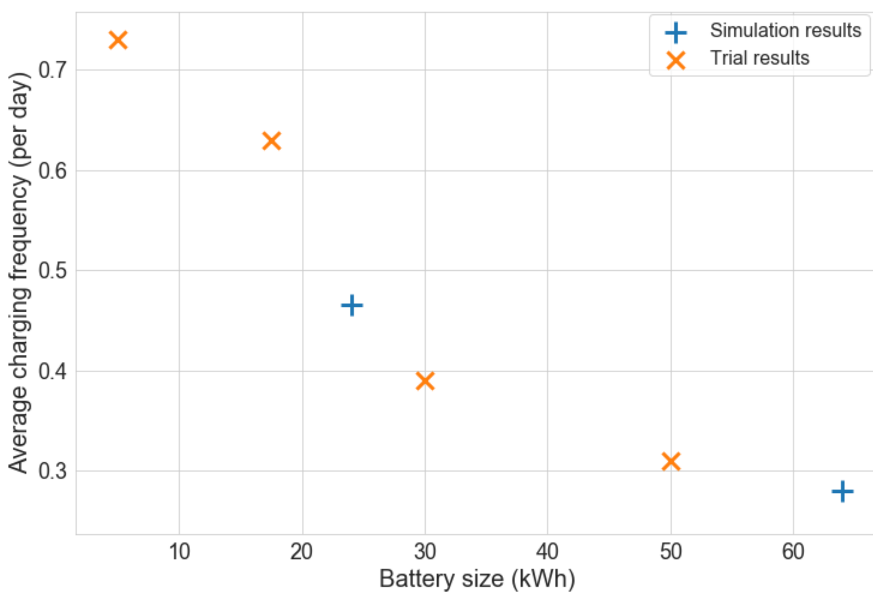

Figure 4: Scatter plot showing average charging frequency (events per day) against vehicle battery size for *Electric Nation* trial data and results from the simulation (minimal charging) in this study

Figure 4 shows that the pattern of a reduction in charging frequency for increasing battery size holds true for the simulation in this study when using the minimal charging scenario. Note that when using the routine charging method, the frequency of home plugins will not change as drivers will always plug-in at home; their charging frequency will be equal to the average number of times they arrive at home in a day.

3.6. Routine charging model

The routine charging model represents a scenario in which EV charging at home is seen to carry negligible inconvenience (i.e. it has become 'routine') such that vehicles are always plugged in on arrival at home regardless of their remaining range or upcoming trips. Table 3 shows a schedule of charge events produced using the routine charging model for the same NTS travel diary in Table 1.

Table 3: Routine charging schedule derived from NTS travel diary in Table 1 for an EV with a battery capacity of 24 kWh and a home charger rated at 3.7 kW AC

Trip #	**Charge Type**	t^{in} (**Plug-in**)	t^{out} (**Plug-out**)	E^{start} **(kWh)**	E^{end} **(kWh)**	P^{max} **(kW)**
2	home	Tu 11:00	Tu 18:15	10.36	24	3.7
4	home	Tu 18:25	Tu 19:40	23.86	24	3.7
6	home	Tu 19:55	W 09:30	23.86	24	3.7
8	home	W 10:45	Su 07:40	22.36	24	3.7

In Table 3, the EV charges at all the home-based opportunities it gets: in this example, whereas it did not charge after trips 4, 6 and 8 under the minimal scenario, it did charge after these trips in the routine scenario. As a result, its energy requirements for these charge events tends to be less. Given that the total charging time is dictated by the duration of the parking event, charging under the routine model of charge event scheduling is typically more flexible than charging under the minimal model.

3.7. Vehicle to grid optimisation

The problem formulation used in this paper is designed to represent how EV chargers could be remote controlled by 'load controllers' – electricity market actors such as aggregators and suppliers – when faced by changing market conditions (this is of increasing relevance when the supply of electricity becomes increasingly variable). The value passed onto the customer

– in the form of a set of variable import and export tariffs – is the cost to be minimised in the optimisation.

The V2G model presented in this paper takes charging schedules from a fleet of EVs (i.e. aggregated sets of data as shown in Tables 2 and 3) to return a solution in which EVs schedule their charging and discharging subject to an import and export tariff in seeking the minimum possible cost of charging, while meeting the same energy gain as it would have under uncontrolled charging at minimum cost. Firstly, the charging schedules are transformed into flexible charging events that cover a 24-hour period in 10 minute timesteps. The 24-hour period chosen represents the period from 12 noon on Tuesday to 12 noon on Wednesday in the 7-day long NTS diaries; the resulting 10 days of flexible charging events are matched randomly to aligned 24-hour datasets of tariffs and carbon intensity (which were both linearly interpolated to produce 10-minutely data).

The optimisation is based on a time-coupled linearised optimal power flow formulation, in which EVs schedule their charging and discharging subject to an import and export tariff in seeking the minimum possible cost of charging. The formulation of this problem is described in sections 3.7.1-3.7.3, and was solved with the CPLEX solver using OATS [37]. The reader is directed to [37] for a thorough literature review on optimisation methods available for the optimal power flow problem and justification for the approach in this paper.

3.7.1. Objective Function

The objective function to be minimised is the sum of the costs of importing or exporting power in each timestep over the sum of charge events (1).

$$\min \sum_{t \in \mathcal{T}} \sum_{e \in \mathcal{E}} (c_t^{\text{imp}} p_{e,t}^{\text{imp}} - c_t^{\text{exp}} p_{e,t}^{\text{exp}}) \Delta t \tag{1}$$

where $\mathcal{T}$ is the time horizon (the set of 10 minute timesteps indexed by t); $\mathcal{E}$ is the set of charge events across all EVs in the fleet; c_t^{imp} and c_t^{exp} are the import and export tariffs respectively at timestep t; $p_{e,t}^{\text{imp}}$ and $p_{e,t}^{\text{exp}}$ are the grid-side active power imports and exports to and from an EV in charge event e respectively to charge or discharge its battery in the time period $[t, t+1]$ (note that both $p_{e,t}^{\text{imp}}$ and $p_{e,t}^{\text{exp}}$ are strictly positive); Δt is the length of the time period $[t, t+1]$ (10 minutes).

The objective function in (1) is minimised subject to the constraints in (2-9).

3.7.2. Power Flow

The power balance equation is given as (2), $\forall\ b \in \mathcal{B}, t \in \mathcal{T}$:

$$\sum_{g\in\mathcal{G}} p^{\mathrm{G}}_{g,t} = \sum_{e\in\mathcal{E}} (p^{\mathrm{imp}}_{e,t} - p^{\mathrm{exp}}_{e,t}) + \sum_{d\in\mathcal{D}} p^{\mathrm{D}}_{d,t} + \sum_{l\in\mathcal{L}} p^{\mathrm{L}}_{l,t} \tag{2}$$

where $\mathcal{B}$ is the set of busbars in the network; $\mathcal{D}$ is the set of domestic demands (i.e. one per household); $\mathcal{L}$ is the set of lines in the network; $p^{\mathrm{G}}_{g,t}$ is the active power contribution from the grid supply point g in the time period $[t, t+1]$; $p^{\mathrm{D}}_{d,t}$ is the active power drawn by domestic demand d in the time period $[t, t+1]$; $p^{\mathrm{L}}_{l,t}$ is the active power flow on line l in the time period $[t, t+1]$.

The power flow equations are given as (3a-3b), $\forall\ l \in \mathcal{L}, t \in \mathcal{T}$:

$$p^{\mathrm{L}}_{l,t} = -\mathrm{B}_l \left(\delta_{b,t} - \delta_{b',t}\right) \tag{3a}$$

$$-\mathrm{S}^{\max}_l \leq p^{\mathrm{L}}_{l,t} \leq \mathrm{S}^{\max}_l \tag{3b}$$

where B_l and $\mathrm{S}^{\max}_l$ are the susceptance and power rating respectively of line l, and $\delta_{b,t}$ and $\delta_{b',t}$ are the voltage angles at b and b', denoting the busbars at either end of line l, in the time period $[t, t+1]$.

3.7.3. EV Charging Model

The energy storage content $E_{e,t}$ of an EV during charge event e at timestep t is related to that in the previous timestep and the energy gained or lost in Δt by (4).

$$E_{e,t} = (\eta p^{\mathrm{imp}}_{e,t} - \frac{1}{\eta} p^{\mathrm{exp}}_{e,t})\Delta t + E_{e,t-1} \tag{4}$$

where the one-way charger efficiency η (for both charging and discharging) is taken as 90%, in common with values for home charging observed in [38] – and as cited in [19].

The EV's battery energy content upon plug-out must be greater than or equal to what it would have received under an uncontrolled charging event (i.e. from Tables 2 or 3) (5); furthermore, the energy content is constrained between 0 and the battery capacity $\mathrm{E}^{\max}_e$ of the EV in charge event e, $\forall\ t \in \mathcal{T}$ (6).

$$E_{e,\mathrm{t}_e^{\mathrm{out}}} \geq \mathrm{E}_e^{\mathrm{end}} \tag{5}$$

$$0 \leq E_{e,t} \leq \mathrm{E}_e^{\max} \tag{6}$$

The power imported to an EV is constrained by a constant current – constant voltage (CC-CV) charging profile typical of lithium ion batteries [39–41], in which the maximum charging power is equal to the rated power $\mathrm{P}_e^{\max}$ for a battery SoC up to γ_e, after which it linearly decreases to zero at an SoC of 1. In this work, γ_e is set to 0.8 in accordance with a real lithium ion battery charging profile from an ABB charger as presented in [41]. The charging power constraint is stated formally in (7), $\forall\ t \in \mathcal{T}$.

$$p_{e,t}^{\mathrm{imp}} \leq \begin{cases} \mathrm{P}_e^{\max}, & \sigma_{e,t} \leq \gamma_e \\ \left(\dfrac{1-\sigma_{e,t}}{1-\gamma_e}\right)\mathrm{P}_e^{\max}, & \sigma_{e,t} > \gamma_e \end{cases} \tag{7}$$

where $\sigma_{e,t}$ is the state of charge of an EV during charge event e at timestep t, calculated as in (8).

$$\sigma_{e,t} = \frac{E_{e,t}}{\mathrm{E}_e^{\max}} \tag{8}$$

The power exported from an EV is constrained by (9).

$$p_{e,t}^{\mathrm{exp}} \leq \mathrm{P}_e^{\max} \tag{9}$$

3.7.4. Calculation of cost and carbon intensity

The cost C_e^c of each charge event e is obtained using (10) with a solution obtained after solving the V2G model.

$$C_e^c = \frac{\sum_{t\in\mathcal{T}}(c_t^{\mathrm{imp}} p_{e,t}^{\mathrm{imp}} - c_t^{\mathrm{exp}} p_{e,t}^{\mathrm{exp}})\Delta t}{\mathrm{E}_e^{\mathrm{end}} - \mathrm{E}_e^{\mathrm{start}}} \tag{10}$$

The carbon intensity $C_e^{\mathrm{CO_2}}$ of each charge event e is given by (11).

$$C_e^{\mathrm{CO_2}} = \frac{\sum_{t\in\mathcal{T}} c_t^{\mathrm{CO_2}}(p_{e,t}^{\mathrm{imp}} - p_{e,t}^{\mathrm{exp}})\Delta t}{\mathrm{E}_e^{\mathrm{end}} - \mathrm{E}_e^{\mathrm{start}}} \tag{11}$$

where $c_t^{\mathrm{CO_2}}$ is the carbon intensity of the grid at timestep t. A negative cost value implies that the EV made revenue over the course of a charging event, by exporting in times of high export price and importing in times of low import price. Likewise, a negative carbon intensity value implies that the vehicle exported during times of high carbon intensity (of which, the carbon intensity would be equal to the the imports minus exports multiplied by the carbon intensity at the relevant times (11)) and imported during times of low carbon intensity. In this way, the provision of power from the EV's battery can be seen as reducing the need for the dispatch of high-carbon generation elsewhere in the system.

4. Results

4.1. Correlation between price and carbon intensity

Figure 5 shows the level of correlation observed between grid carbon intensity and tariff, shaded by time of day (00:00 - 23:50). The left-hand plot shows both import and export tariffs; the right-hand plot shows the difference between import and export to highlight the conditions in which consumers will be paid a higher price to export than they would pay for import.

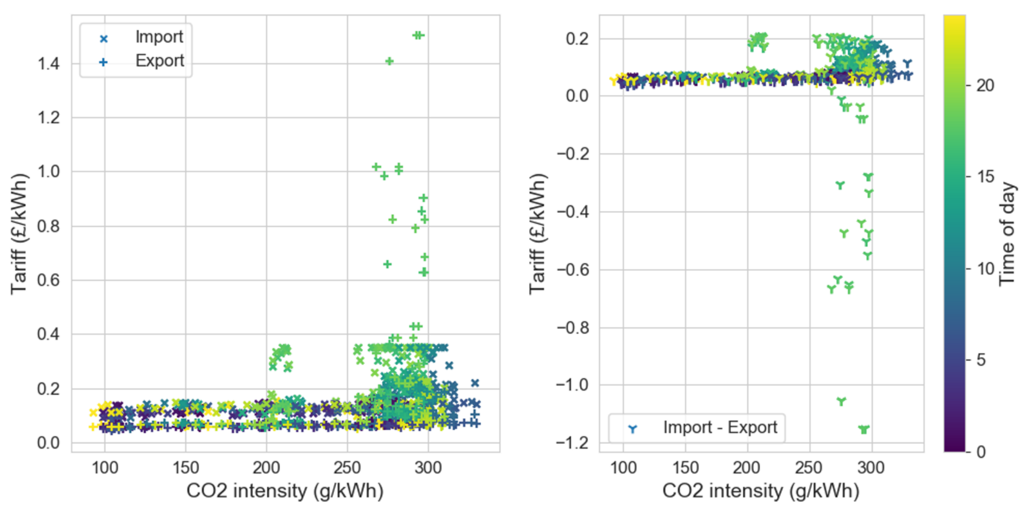

Figure 5: Scatter plots showing (left) import & export prices vs. carbon intensity and (right) the relative difference between import & export price vs. carbon intensity – both plots coloured by time of day

Two patterns are observable from Figure 5. Firstly, there is a weak non-linear positive correlation between carbon intensity and both import & export tariffs. There are two spikes visible on both plots, corresponding to times when the price of electricity rose far above the nominal range. The cluster of points to the right of the CO_2 intensity axis in the left-hand plot shows that electricity tends to be more expensive when the source is high carbon. Secondly, there is a visible affect of time of day on both tariff and CO_2 intensity. The vast majority of points during times of high price correspond to the peak demand time of 16:00-20:00; on the other hand, the vast majority of points corresponding to a CO_2 intensity of under 150 g/kWh are at night, between 22:00 and 06:00. These two patterns are advantageous for a V2G scheme, as EVs are more likely to be plugged in overnight.

4.2. Demand profiles

4.2.1. Minimal charging

Figure 6 shows the baseline (uncontrolled) EV charging profiles alongside domestic demand and grid carbon intensity for all 10 days under study in January 2021; Figure 7 shows the same data for the results of the V2G optimisation.

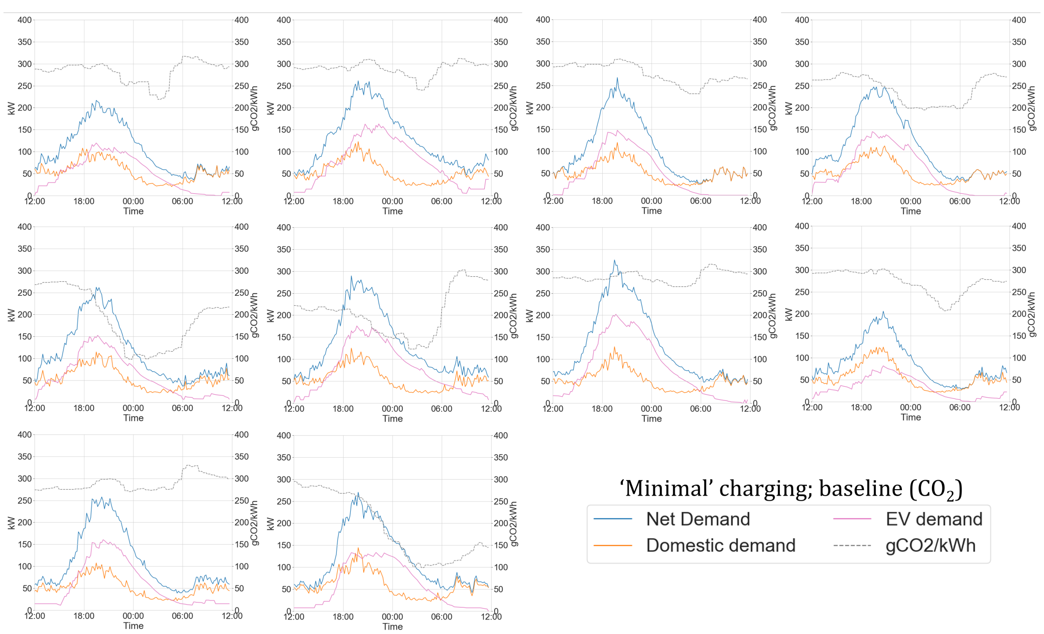

Figure 6: Baseline (uncontrolled) EV charging, domestic demand and grid carbon intensity for 10 days under study in January 2021 – minimal charging model

Figure 6 highlights the level of diversity that can be expected in uncontrolled EV charging. While there is clearly some variation day to day with the peak magnitude varying by as much as 50% between days, the peak always occurs within 19:00-22:00; when combined with the domestic demand which tends to peak earlier at 18:00-20:00, the total net peak occurs at 19:00-20:00. In all 10 days under study, the minimum CO_2 intensity occurs during the night, within the window 22:00-06:00.

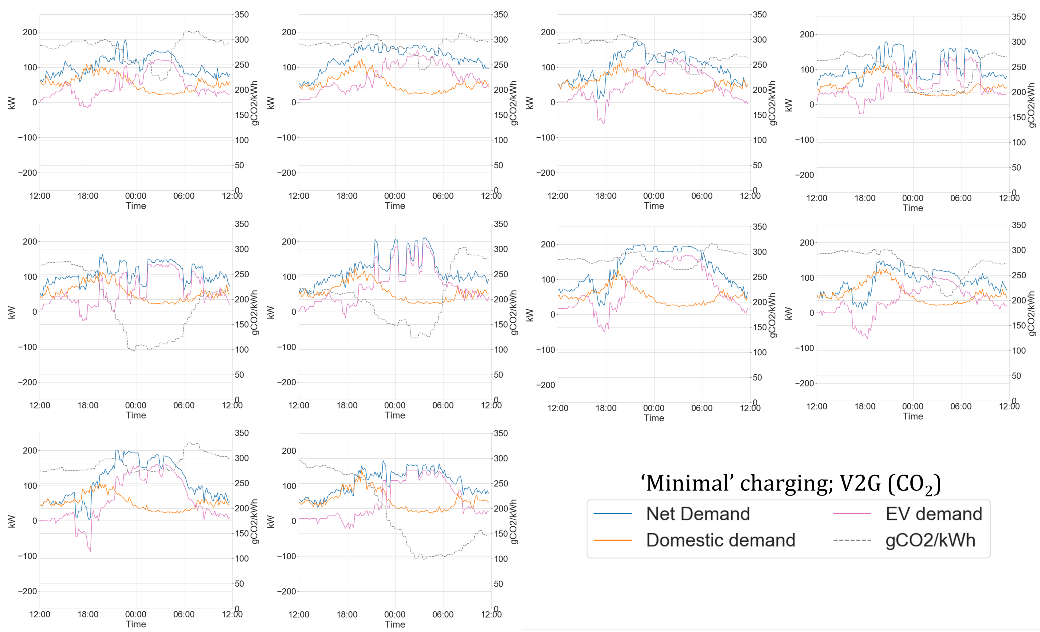

Figure 7: V2G-controlled EV charging, domestic demand and grid carbon intensity for 10 days under study in January 2021 – minimal charging model

Figure 7 shows the extent to which EV charging could be controlled in a V2G scheme if EVs were plugged in only when they 'need' to (section 3.5). The total EV demand goes negative (export) on all but 1 day under study, due to either i) a higher export tariff than import at that specific moment in time or ii) a chance to sell (via the export tariff) and buy at a cheaper price at a different moment in time (subject to the constraints in (2-9)). The export always occurs in the time period 17:00-19:00, where the export price is highest (Figure 2). In all 10 days under study, the peak EV charging demand occurs in the dead of night (02:00-05:00) – representing the time when the maximum resource (number of EVs) is plugged in and the import tariff is generally lowest. As shown, this often corresponds with troughs in grid CO_2 intensity.

4.2.2. Routine charging

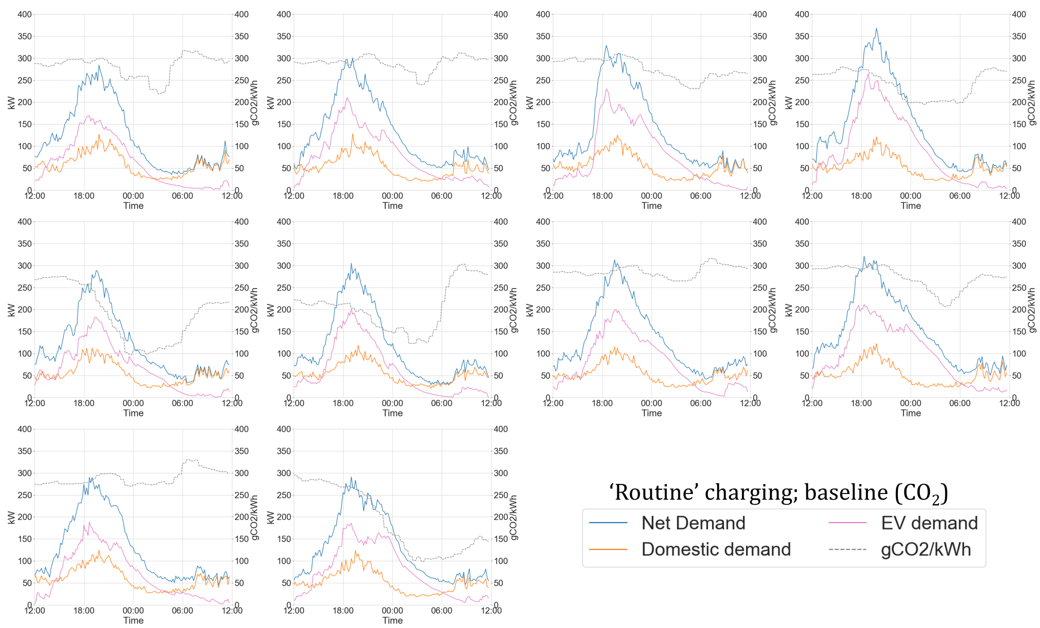

Figure 8: Baseline (uncontrolled) EV charging, domestic demand and grid carbon intensity for 10 days under study in January 2021 – routine charging model

Compared to the baseline charging demand for the minimal case (Figure 6), Figure 8 shows the trend toward less diversity in uncontrolled EV charging – to be expected, as every EV is plugged in on every arrival at home. The result is that the peak magnitude varies by only approx. 30% across the days, compared to approx. 50% in Figure 6. The peak is also shown to be generally higher for the routine case, but with a sharper decline during the night. This is because while more EVs plug in and begin charging in the evening, their energy requirement tends to be lower and so they reach 100% SoC faster than in the minimum case. As already discussed, this shows that the routine charging model produces more flexible EV charging: any controller has a longer time to achieve a given energy increase.

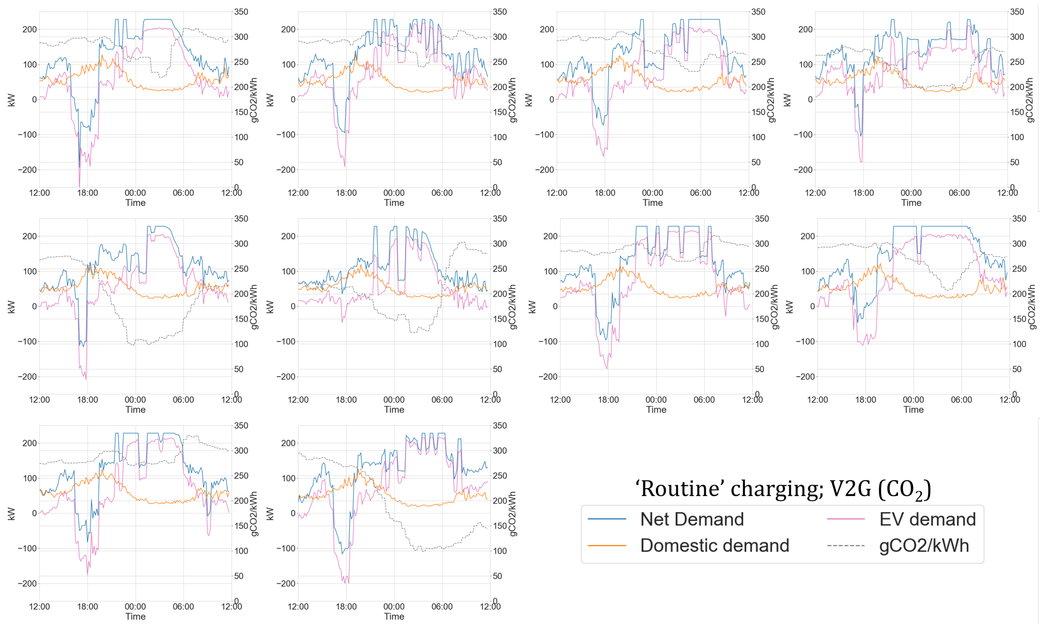

Figure 9: V2G-controlled EV charging, domestic demand and grid carbon intensity for 10 days under study in January 2021 – routine charging model

In comparison to the V2G-controlled minimal charging case (Figure 7), Figure 9 shows a much higher degree of export from the EV fleet: the combined demand from EVs goes negative on all 10 days, and the average peak export magnitude is over twice as great. The net demand profile in both Figures 7 and 9 are clearly constrained by the network, resulting in the flat plateau-style traces visible in many of the plots.

It should be noted that whilst the sudden swings visible in Figure 7 and (especially) Figure 9 are advantageous for reducing the price paid for electricity, they are potentially more difficult for an ESO to predict and could lead to degradation in grid stability, including sudden swings in grid frequency. To remedy this, flexible demand (such as V2G-controlled EV chargers) could be subject to randomised offsets in its response to changes in dynamic tariffs such as the Octopus *Agile* tariffs used in this study. This approach, favoured as part of the BSI PAS 1878 emerging standards for domestic smart appliances [42], would have some effect on the ability to minimise cost of charging as per the method in this study. A valuable piece of further work would be to investigate the impact of mandating such standards on the potential flexibility of responsive demand such as V2G.

4.3. Price paid and carbon content

Figure 10 shows cumulative distribution functions (CDFs) of the average price paid by an EV (left) and the average carbon intensity (right) of the EV's net energy import during a given charge event.

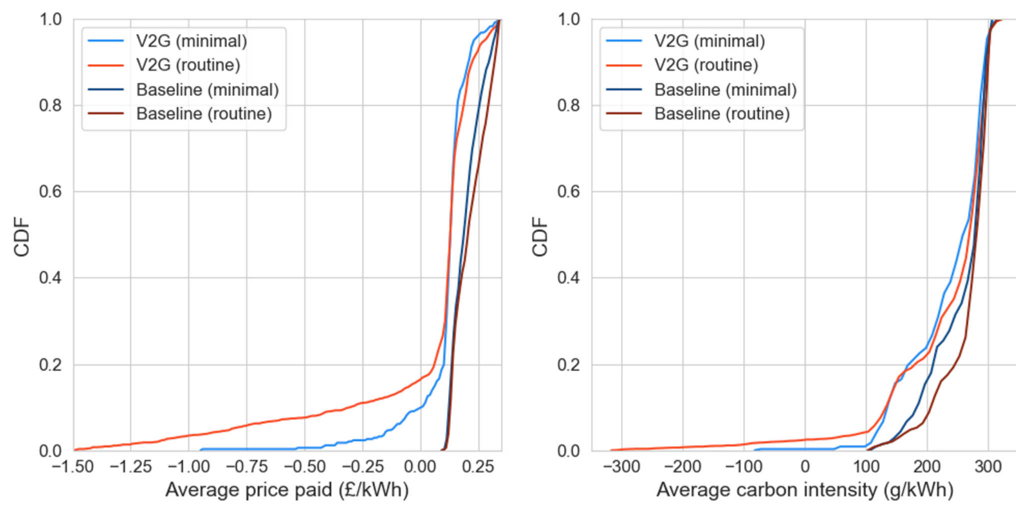

Figure 10: Cumulative density functions (CDFs) showing the price paid (£/kWh) and carbon intensity (g/kWh) for baseline (uncontrolled) and V2G-controlled EV charging for 10 days under study in January 2021

Figure 10 shows the ability of V2G to reduce the price paid and carbon intensity of electricity used to charge an EV's battery for both the minimal and routine modes of charging. It it shown on the left-hand plot of Figure 10 that virtually every EV across all the trials paid less using V2G than when charging according to the baseline. On the other hand, around 60% of EVs were able to reduce the carbon intensity of the electricity they receive versus the baseline case. The horizontal axes on both plots is shown to extend into the negative of their dimensions. The left-hand plot shows that approx. 10% of EVs were able to make a profit under the minimal charging model, rising to 17% of EVs under the routine charging model. A negative carbon intensity value on the right-hand plot implies that the vehicle exported during times of high carbon intensity (of which, the carbon intensity would be equal to the the imports minus exports multiplied by the carbon intensity at the relevant times (11)) and imported during times of low carbon intensity. Figure 10 shows that, although price and carbon intensity are correlated (Figure 5), the potential for V2G to reduce the carbon intensity of electricity used to charge an EV is not as great as its ability to reduce cost: only 7% of EVs were able to achieve a negative carbon intensity using V2G under the routine charging model; this was a negligible amount under the minimal charging model.

The mean values of the distributions in Figure 10 are shown on Figure 11 alongside horizontal lines representing the mean import tariffs and carbon intensities for different time periods, to highlight how V2G can reduce the price paid for electricity and support decarbonisation of the electricity system by importing low carbon electricity and exporting it back at times of high carbon intensity.

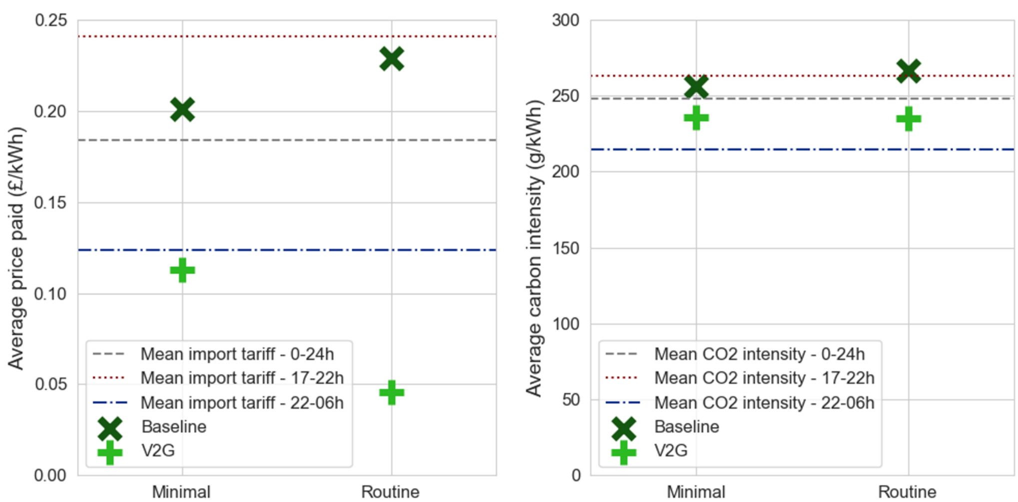

Figure 11: Comparison of average price paid (£/kWh) for baseline (uncontrolled) and V2G-controlled EV charging for 10 days under study in January 2021 – with average tariffs shown for reference

Comparing the baseline (dark 'Xs') in Figure 11, it can be seen that the price paid and the carbon intensity are higher for the routine case than for the minimal case. This is because, under the routine case, EVs are more likely to have completed their charging in the high-priced and typically high-carbon evening peak, whereas if EVs have a larger energy requirement as per the minimal case they are more likely to be charging later in the night when the price and carbon intensity are lower.

Figure 11 shows that, when optimised for minimum cost, V2G can reduce the price paid for electricity by significantly more when the EV is plugged in every time it arrives home compared to if it is plugged in according to the minimal charging model. Of course, a customer who was not having their EV controlled would be unwise to opt for a dynamic tariff such as Octopus *Agile*; they would be more likely to opt for a flat tariff. Comparing the values in Figure 11 to Octopus' flat tariff for South Scotland of £0.157/kWh (correct as of April 2021) [43], it was found that:

- V2G charging, if optimised for monetary cost, was found to reduce the price paid for electricity by 30% on average if EVs are only plugged in when they 'need' to (i.e. in accordance with the minimal charging model) and 68% on average if EVs are plugged in every time they arrive home.

- V2G charging, if optimised for monetary cost, was found to reduce the carbon intensity of electricity supplied by 8% on average if EVs are only plugged in when they 'need' to (i.e. in accordance with the minimal charging model) and 12% on average if EVs are plugged in every time they arrive home.

5. Discussion

The results presented in section 4 show how the potential flexibility of EV charging changes depending on how often drivers plug their vehicles in. Clearly, when drivers plug their vehicles in 'routinely' (whenever they arrive home), there is greater potential to shift demand in time and respond to system-wide requests. Aside from reducing consumer bills and the carbon emissions associated with charging, it increases the level of storage resource available to the system. The approach demonstrated in this paper can be used by aforementioned load controllers (aggregators or suppliers) to predict the level of resource they can offer as part of balancing services. The total storage resource from V2G is a function of the number of EVs plugged in, their SoC and network constraints (the latter related to the spatial distribution of the EVs). While increasing plug-in frequency will lead to an increasing storage resource, the relationship will not be linear: as cars are plugged in more often, they are more likely to be plugged in with a higher SoC (for a given set of travel requirements) – and hence more likely to be charging in the constant voltage (CV) region of the CC-CV charging profile as typical for lithium-ion batteries. The network constraints are also clearly curtailing some of the contribution from V2G in this example, visible through the flat plateau-style traces visible in Figures 7 and 9.

The results in section 4 are based on the premise that every V2G-controlled charge event must enable the same energy transfer as would have been possible in a 'dumb' charging event – in most cases, one that takes them to 100% SoC. However, as exemplified by Table 1, the majority of trips taken by drivers are not sufficient to totally deplete even a modestly-sized EV battery of charge; it would be reasonable to expect, therefore, that drivers could seek a lower energy transfer in return for increasing revenues/reduced costs – so long as it would be sufficient to meet the energy demand of their next journey away from home.

The results in section 4 show a modest reduction in CO_2 emissions associated with charging. However, the main contribution to decarbonisation from V2G is by providing balancing services to the electricity system – these will be increasingly valuable as the proportion of converter-interfaced generation increases [44]. Therefore, by incentivising drivers to plug their vehicles in every time they arrive home, load controllers can offer a greater amount of flexible resource to the electricity system.

Of course, use of the battery in V2G is not free – charging and discharging the battery for V2G ultimately uses up the cycles within a battery's useful life. While this matter has been a subject of much debate – including some evidence that there is potential to actually increase useful battery life through V2G [45, 46], a review in [47] puts the cost of V2G associated with battery degradation in the range £0.03-0.09/kWh. In comparison to the average savings made from V2G as found in this study versus the comparable flat tariff – £0.04/kWh and £0.11/kWh from the minimal routine charging models respectively (Figure 11), it is shown that V2G is likely to be commercially viable under existing tariff arrangements if vehicles are plugged in every time they arrive home.

6. Conclusion and further work

This paper has presented an assessment of the potential for V2G to reduce consumer bills and the carbon emissions associated with charging by linking travel data to a time-coupled linearised V2G optimisation model via two separate charging behaviour models – a 'minimal' model in which drivers seek to minimise their number of plug-ins, and a 'routine' model in which drivers plug in every time they arrive at home. It was found that, on the basis of the time range studied, V2G can reduce the average price paid for EV-charging electricity by 30-68% versus a flat tariff – with the lower end of that range representing a case where consumers only plug in when they 'need' to, and the higher end representing the case where consumers plug in whenever their cars are at home. It was also found that due to the positive correlation between price and carbon, optimising for price also resulted in reductions in carbon intensity of the EV-charging electricity by 8-12%, with the range representing the same cases as before.

The 10 days under study in this paper are in January 2021, which (as typical of the winter) represents generally high electricity prices and high carbon intensity. V2G operation would be expected to vary around the year as both electricity demand and renewable resource available change. Furthermore, these patterns would be expected to change in the future as the UK continues to install greater capacities of variable renewable generation. Therefore, a piece of recommended further work from this paper would be to apply the model to different times of the year to build up a more complete picture of how consumers would (financially) interact with V2G.

An additional piece of recommended further work is to directly quantify the relationship between plug-in frequency and total storage resource from V2G: as already discussed, this is a function of the number of EVs plugged in, their SoC and network constraints (the latter related to the spatial distribution of the EVs). As network architectures would have a significant effect on network constraints, this would need to be done for a set of electricity networks: it is recommended that a set of 'archetypes' be chosen to represent the variety in network design in GB.

The final piece of recommended further work is to examine the influence of changing travel patterns on the results of this study. While the NTS data used in this study is a useful resource for current car-based travel habits, the potential for this to change in conjunction with the electrification of private vehicles (and the decarbonisation of the wider economy) is undeniable. Firstly, significant changes in travel behaviour from the ongoing COVID-19 recovery may last into the long term [48]. Secondly, a reliance on a switch to EVs without any reduction in car use would be likely to result in the UK missing its 2050 Net Zero target [49], and therefore increases in public [50, 51] and active [52] transport are equally vital parts of the transport system decarbonisation strategy as electrification of private vehicles. Therefore, potential futures of car ownership and travel behaviours should be included in the analysis for the potential of EV/power system integration and the role of V2G to support electricity system decarbonisation.

Acknowledgement

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