# *EV smart charging: how tariff selection influences grid stress and carbon reduction*

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# EV smart charging: How tariff selection influences grid stress and carbon reduction

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HIGHLIGHTS:

- Assesses grid impact of EV charging under diverse tariff and control strategies.
- Stepwise Time of Use tariffs cause higher peak loads than on-demand EV charging.
- Smart tariffs reduce grid carbon emissions with dynamic tariffs most effective.
- Diversity of tariffs should be encouraged to mitigate the risk from demand peaks.
- Smart tariffs fail to avoid local EV peak loads with capacity management necessary.

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ABSTRACT

With the rapid increase in ownership of Electric Vehicles (EVs), widespread concern has been raised regarding the potential for EV charging demand to overload electricity grids. Smart control of charging is advocated as a solution, gaining attention from business and support from policymakers. However, the ultimate grid benefits (or disbenefits) of smart charging will follow from a combination of user behaviour and pricing arrangements / tariffs. Local clustering of vehicle uptake can lead to unintended consequences as national incentives fail to align with local pressures. In this paper, we describe a simulation of the dynamic electricity demand pattern arising from a fleet of grid connected EVs. The model developed for this study combines stochastic sampling of data from a UK-based smart charging trial (Western Power Distribution's Electric Nation project) with a set of plausible tariffs, including a strategy which specifically seeks to minimize grid carbon emissions. This provides insights into the potential impacts of EV charging by encompassing a wider range of tariffs than previously assessed, while also separating the control actions of optimising cost and managing capacity. We examine the carbon implications of tariff choice and introduce a range of grid overload metrics that reveal nuances in the tariff implications and evolution of impacts as EV penetration increases. The results show that smart charging is not necessarily a better solution for the grid compared to on-demand charging. Stepwise tariffs, currently favoured by UK energy suppliers, present a particular risk. Such tariffs can tend to increase load synchronization by shifting load towards periods where more cars are connected and awaiting charge. This can lead to an increased peak load even at moderate EV uptake levels. Dynamic tariffs proved preferable but still increase peak demand at higher vehicle uptakes. All smart tariffs offer a strong carbon benefit, but, again, current stepwise tariffs are failing to realise the full potential that could be realized by targeting low carbon time periods. Separate local capacity management was able to eliminate overload at the secondary substation, even with very high EV uptake, with only rare, very small levels of unserved demand.

## 1. Introduction

The impact of EV charging is featuring not only in a wide range of research but also as a significant strand in government energy policy and commercial service development. Deregulated energy systems, such as the UK, are facing rapid changes in demand dynamics alongside a diverse array of emerging consumer tariffs and services which may in turn be enabled or restricted by interventions from the electricity system

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operator and network owners. While benefits can be envisaged in terms of carbon reduction, cost saving and security, this changing landscape brings the risk for unexpected negative consequences to result from conflicting incentives or dramatic coincident behaviours.

Widespread concern has been raised regarding the potential for EV charging loads to overload electricity grid capacity. Attention is often given to overlap with peak demand periods established before vehicle electrification, typically in the early evening. Many earlier studies assessed the impact of uncontrolled (or on-demand) charging, assuming that vehicles would be charged at their maximum rate from the moment that users choose to connect them to a charger. For example, [1] simulated the impact of uncoordinated home charging on the residential load in a US distribution network, noting that the charging rate plays a significant role at a low voltage level and can decrease the expected life of the transformer. By contrast, [2] observed that studies which assume that EVs plug in every day, after their last daily trip, can overestimate the charging load and the cost of distribution grid upgrades required when more diverse behaviour is considered, even if uncontrolled charging is maintained. A further study [3] used data from a UK based trial for EV charging behaviour and illustrated that the distribution grid has a higher capacity to accommodate EVs compared to the studies that base their analysis on more rigid assumptions around charging behavior, even with uncontrolled charging.

As EV connection time is usually longer than the time needed to transfer the required demand [4], consideration can be given to controlled (or smart) charging. Controlling the time and rate of charging has potential to shift EV load to times with lower demand from other services and reduce negative impact on the grid. As well as numerous research studies, controlled charging solutions are now advocated by policymakers (as seen, for example, with the UK Electric Vehicles (Smart Charge Points) Regulations 2021 [5]) and being developed by a diverse range of private enterprises including energy utilities and vehicle manufacturers. One study [6] assumed that the utility can optimize the EV charging load to minimize its impact on the grid assets with power system level communication. The authors show that their proposed approach significantly increases the number of EVs that can be charged at a specific time. Meanwhile [7] quantified the impact of possible conflict from smart charging with respect to distribution network and transmission network criteria. They concluded that smart charging could avoid the need for additional generation capacity in the UK. Moreover, the percentage of the distribution grid that requires upgrade decreases to 9% with smart charging compared to 28% with uncontrolled charging. Another team [8] studied the impact of non-systematic EV connections, i.e. EVs do not connect to be charged every day necessarily, versus everyday connection peak load and flexibility potential.

While recognizing the value of controlled charging, some authors have begun to point to the potential for unintended consequences. Much of this has been revealed through assessments of the likely influence of various tariff options or pricing arrangements. Two newly introduced static Time of Use (ToU) tariffs, specifically designed for EV charging in the commercial and industrial sectors, are assessed in [9]. Their analysis indicates that these tariffs create new peaks in otherwise off-peak hours and are inefficient in reducing load on grid assets. [10] made a similar conclusion for ToU tariffs and concluded that uncontrolled charging is preferable to a two-step tariff. Times of high wind generation in the Netherlands are examined in [11], with the authors observing that the electricity price will fall and local network loads could be unduly high due to increased EV charging. They concluded that non-systematic plug-in should reduce this adverse impact on the distribution grid, though in turn this can reduce the real charging flexibility available, especially for EVs with larger batteries and lower plug-in frequency. Multiple charging strategies were modelled in [12], alongside different load caps to evaluate the lifetime of transformers in a workplace. They concluded that optimizing just for ToU rates creates higher peaks which is worse than uncontrolled charging for the transformer and emphasize the importance of capping total load. The impacts of ToU and time-of-export tariffs for solar home batteries were analyzed in [13], with concerns raised that the peak at low voltage level is not sufficiently reflected by ToU tariffs. They identify the risk that overnight load could increase due to overnight battery charging when solar is not utilized and conclude this consequence could increase for EV charging given their inherently larger batteries. The effect of Swiss EV penetration levels on utilization of high-voltage substations were studied in [14]. The authors used driving statistics to estimate the charging requirements with static and dynamic pricing regimes, and also modelled the impact of load on price by using a regression model. They conclude that consumers managing their charging based on dynamic prices will reduce substation overloads compared to static (flat) prices, in a scenario with a low renewable energy capacity increase. However, in a scenario with high renewable generation, dynamic prices can lead to increasing high-voltage grid overload.

There has been a growing recognition that identifying the time period when electricity is drawn from the grid is significant in attributing grid related carbon emissions to demand. Notwithstanding widespread use of the term “Zero Emission Vehicle” the act of driving an EV brings responsibility for carbon emissions arising from power stations that generate the requisite amount of electricity. Annual average grid carbon intensity values have become widely established in carbon footprint calculations (for UK data, see [15]). More recently, calls have come for carbon assessment to reflect the time varying nature of the grid generation mix, with researchers [16,17] advocating dynamic approaches. Such proposals neglect the nuances of assessing marginal impact, as described in [18] and further quantified in [19]. However, there can be incompatibilities between the dynamic and marginal approaches; at the time of writing, short term marginal generation in the UK is almost always gas fired, so this metric would offer little value to an assessment seeking differences in time of use. While neglecting the true marginal impact, a grid averaged dynamic approach gives a clearer credit for flexibility initiatives that seek to align electricity demand with preferential times for low carbon generation. Accordingly, grid average dynamic values are featuring alongside calls for flexibility measures, as reflected by the UK ESO’s publication of time varying carbon intensity [20].

In the work described below we build on the body of smart charging research by exploring the influence of a wider range of plausible tariff structures. Given that none of the tariffs tested fully avoid an increase in peak demand, the paper proceeds to assess their interaction with an independent network capacity control. We have used data from a real-world smart charging trial to condition a stochastic model for generating charging demand, connection times and charging data. This approach connects control strategies with data on real user behaviour and improves on studies which assume common user behaviour by introducing heterogeneity in the frequency of charging, charging demand and time of plug-in.

This work advances understanding of EV charging impacts by (i) drawing on a diverse range of plausible tariffs, including stepwise and fully dynamic ToU tariffs, (ii) distinguishing between price based control strategies and separate local capacity management actions and (iii) examining how the various charging regimes affect carbon emissions as well as grid loading. In regard to aspect (i), studies mentioned above have addressed a wide range of tariffs but only dealt separately with stepwise [8,9,10,12,13] and fully dynamic [14] tariffs. For (ii), while certain studies compare price and capacity optimisation, they assume a single controller who can choose which aspect to focus on [11,12]. This is entirely reasonable for the workplace scenario addressed by [12]; however for domestic charging these factors will often fall to different stakeholders and may be managed entirely separately. At present in the UK, various tariffs are offered by national energy suppliers reflecting temporal dynamics of wholesale energy trading. Meanwhile local capacity management requires separate intervention from a network owner, with a variety of mechanisms reflected through local trials. Our research design seeks to explore this disconnect. For (iii), although the time varying nature of grid carbon emissions has seen increasing recognition [16,17,20] this has been largely absent from the EV studies noted above. Only [6] addresses this aspect, including carbon in the charging optimisation, albeit based on a fixed daily generation dispatch profile. Further to these three aspects, we introduce a range of grid impact metrics which reveal some surprising nuances to the impact of different combinations of tariff and EV penetration. While this lacks the technical sophistication of the established transformer model used by [12], it brings an insight into grid impacts which is more widely applicable, through avoiding dependence on local network topology and temperature variations. Finally, our study builds on previous research by drawing on data from an extensive EV user trial. With widespread EV adoption being a recent phenomenon, early studies typically relied on travel surveys of fossil fueled cars to derive patterns of driver behaviour [1,10,11,14]. There has been a growing recognition that these approaches neglect uncertain plug in behaviours which are being seen to evolve as EV ranges increase [8]. This has led researchers to use real world trial data wherever possible [2,3,4,7,8,12]. Our study draws on the Electric Nation dataset, as used by [8], one of the largest trial data sets available when our research commenced.

The following section describes the modelling approach and underpinning assumptions. Grid hierarchies and assumptions such as network capacity have been developed in a generic manner so that the approach can be applied to any network structure. In the Results section, we present patterns of electricity demand that arise, alongside key metrics which highlight the impact of tariff choices on grid capacity exceedance and carbon emissions. Finally, cases that present particular risks for the distribution grid are revealed and discussed.

## 2. Modelling

In this paper, we describe the implementation of a model, which assesses the dynamic electricity demand pattern arising from a fleet of connected EVs. Model code has been made available, open source, at [21]. The model is structured to address all relevant network tiers, reflect a variety of tariff / incentive structures and allow representation of demand from a range of sources, not exclusively EVs. In the implementation described here, EV demand is allocated stochastically, with parameters and weightings drawn from a real world EV user trial. The impact of EV load on electricity price is neglected, reflecting a relatively near future situation. Accordingly, attention is restricted to lower-level secondary substations, where clustering of early adoption could reasonably lead to locally increased penetrations of EVs, in advance of the national uptake rate. The UK is targeting all new vehicle sales to be zero emission at point of use by 2030 [22,23]. Meanwhile, EV sales are increasing rapidly, alongside varying support to local charging infrastructure.

The model comprises two main modules, *EV simulation* and *charging dispatch*.

- The EV simulation module establishes: number of houses, number of EVs, allocation of EVs to houses, grid connection location, charger rates and battery capacities. Each charger is designated with a particular tariff. For each EV, plugin / out times and energy requirement are defined separately for every charging session across the whole simulation period. This is implemented as a stochastic simulation that draws on data from the smart charging trial as described in section 2.2.
- The charging dispatch module calculates the preferred time of charging and energy delivered to each vehicle in every time step. The charging strategies and the algorithm for each is explained in section 2.3.

In the implementation described here each house is assigned at most one EV and they all charge at home. Each house is associated with a charger and the charger is connected to a secondary substation in the distribution grid. Secondary substations are connected to primary substations at a higher level based on the number of secondary to primary substations, described next.

### 2.1. Data

The Electric Nation trial data is used in this study for simulating EV requirements [24,25]. In this trial, led by Western Power Distribution in the UK, 673 volunteers were recruited to participate in smart charging trials between January 2017 and December 2018. This trial captured 130,000 charging events and provides a well-established set of data required to better understand how users charge their EVs in practice. This was one of the world's largest EV trials at the point when our investigation began and the data had become recently available.

Each EV-charger combination is allocated to one of a range of tariffs, informing a price which the charge control algorithm seeks to minimise. These represent several current UK electricity tariff structures, as well as a flat price and a preference to minimise carbon intensity (CI), all collectively described as *tariffs* hereafter to avoid repetition:

- Flat: the electricity price is a constant value per kWh over the day, weekday, or weekend (p/kWh).
- Distribution Use of System (DUoS) informed: a stepwise tariff which varies with three time bands (green, amber, and red) across the day. Red represents the highest price, peak demand period (p/kWh).
- Economy 7: a two-price stepwise tariff with lower price available through 7 overnight hours (p/kWh).
- Dynamic: a half hourly (HH) varying dynamic price, with discrete values for each HH period (p/kWh).
- Carbon intensity: HH varying dynamic carbon intensity ($gCO_2$/kWh).

These tariffs (see Fig. 1.b) are not mutually consistent in magnitude, given differences in target customer and time frame; however, it is only the internal pattern within each tariff that governs model behaviour. Accordingly, results are presented only in terms of energy and carbon. The DUoS informed tariff is based on a recent tariff provided by an anonymous commercial user. The only element which varies with time is the DUoS charge, details of which are available at [26]. Typical Economy 7 values and times are shown in Fig. 1(b). To represent a dynamic ToU tariff, we use the Agile tariff from Octopus Energy (a UK energy supplier) taking values from January 2019 as a period with relatively stable energy market behaviour. Agile tariff data is available at [27]. More recent dynamic ToU price profiles have been affected by global issues such as the Covid19 pandemic and recent surges in gas prices. Octopus Energy's *Agile* tariff for December '21 is included in Fig. 1(b) to illustrate this sensitivity of the average daily profile to wider energy market issues. Dynamic ToU tariff profiles are only considered under a relatively stable market, reflecting supplier trends to concentrate on less complex price structures during this period of uncertainty. Of the six energy suppliers listed in a recent UK market comparison site study [28], five offered smart tariffs, with all being two tier, step-wise tariffs offering a cheaper rate in a fixed off-peak time period. In the model, prices are exogenous variables and the interaction between electricity demand and dynamic price is not modelled. UK grid carbon intensity data is available at [29]. Non-EV load is modelled by multiplying the number of houses by domestic load per household captured from the Elexon profile depicted in Fig. 1.a [30].

As well as using carbon intensity data from [29] to inform one of the tariff choices, it is also used later to calculate the grid carbon emissions that can be attributed to charging under each tariff. This reflects the dynamic nature of grid carbon intensity and whether charging occurs at time periods where this is higher or lower.

The results presented in this paper focus explicitly on the impact of EV load at secondary substation level, reflecting a risk that EV uptake in

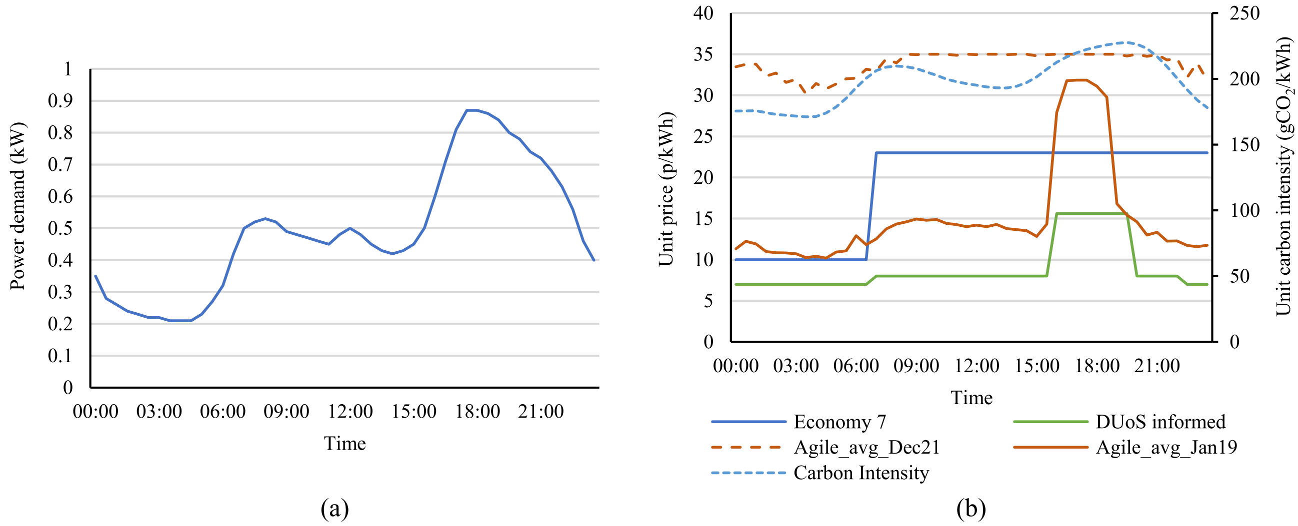


**Fig. 1.** (a) domestic load for unconstrained customer [30], (b) Electricity price in different tariffs in the UK [26,27], average half-hourly carbon intensity in the UK [29].

certain local areas could be much higher than average national levels. Availability of free or low-cost chargers in an area, access to off-street parking, local authority action, commercial targeting or peer to peer encouragement from neighbours could all deliver an uneven spatial influence. Secondary substations represent the infeed to the lowest voltage level in the UK power system. For context, transmission networks typically operate at 400 or 275 kV (in England). Distribution networks connect through Bulk Supply Points which may see an initial voltage reduction before primary substations reduce to 33/11 kV and secondary substations reduce to low voltage, i.e. 433 V across three phases [31]. A generic UK distribution network was described by [32], with each 33/11 kV primary substation supplying six 11 kV feeders and each of these feeders suppling eight 11/0.433 kV secondary substations.

### 2.2. EV simulation

The EV simulation module establishes the EV fleet and their charging requirements over the simulation period ($t_1$, $t_2$). Each vehicle is allocated a battery capacity and the home charger that each is associated with. Charging requirements are set for all charging sessions of the fleet over the simulation period. Here, a charging session is taken as the time period starting when an EV is plugged in and ending when it is next plugged out. Charging sessions are assigned with perfect foresight for the entire simulation period.

In the Electric Nation trial, 42% of EV chargers were rated at 3.6 kW with the remaining 58% at 7 kW (data available at [33], descriptive analysis in [34]). The battery capacity of EVs with 3.6 kW chargers varies from 4 to 30 kWh, while the capacity of vehicles with 7 kW chargers is between 8 and 100 kWh. EVs with larger batteries are typically associated with higher rate chargers. In the model, the charger rates of 3.6 and 7 kW are allocated to EVs randomly, based on their probability in the trial. When the charger rate of each EV is specified, its battery capacity is selected randomly from the list of all battery capacities associated with the specific charger rating. Within the Electric Nation trial, the frequency of EV plug in was seen to be influenced by both the battery capacity and the time of year. Cars with larger batteries plug in less frequently than those with smaller batteries. Moreover, the frequency of connection increases in colder months, potentially due to reduced efficiency coupled with increased heating and lighting demand.

The number of times ($n$) that each EV plugs in over each month depends on the battery capacity range and the month and the number of days of that month. $n$ days are randomly selected from that month. For each plug-in day chosen, the time of plug-in and plug-out needs to be identified. The profile of plug-in times is derived from Electric Nation data. As illustrated in Fig. 2, there is a significant difference between the times of connections during weekdays compared to weekends. Car plug-in time has a high peak between 4 and 8 PM over weekdays, with a more even profile over weekends. The plug-out times were not separately reported in the Electric Nation trial. The plug-out probability profile has been taken as a mirror image of the plug-in profile, centred around midday. This reflects an assumption that users departing earlier are more likely to be away for an extended period such as a commuting journey, while allowing for some shorter trips. It also reflects a high likelihood that cars will be home overnight.

For each charging session, each EV is allocated an energy demand sampled from the real demand data in the Electric Nation trial [33]. Fig. 3 shows the demand per session reported in the trial, grouped by size of battery. It is notable, though not surprising, that the average and spread of charging demand per session is seen to increase with the increase in battery size.

### 2.3. Charging dispatch

#### 2.3.1. Charging schemes

Three types of charging schemes are represented in the model: *on-demand*, *smart*, and *capacity-managed* charging.

- In *on-demand* charging, charging begins immediately the car is plugged in and ends once all required energy has been received.
- *Smart charging* is used here to explicitly refer to the case where charging is managed in order to gain the greatest advantage from a chosen tariff. This effectively represents an automated process that could be affected by an on-site controller or remote third party service provider.
- *Capacity-managed* charging is used here to refer to a separate control step that seeks to avoid overload of an assumed grid capacity. Imposition of a grid limit has the potential that some EVs do not receive their full required energy in an individual charging session.

Under smart charging each user is allocated to one of the tariffs described in section 2.1. Model runs are presented below assuming all users adopt the same one of the five tariffs. A *balanced* case is also modelled with a share of 20% of the users allocated to each tariff.

#### 2.3.2. Smart charging heuristic

A simple heuristic was developed to minimize the carbon or cost of

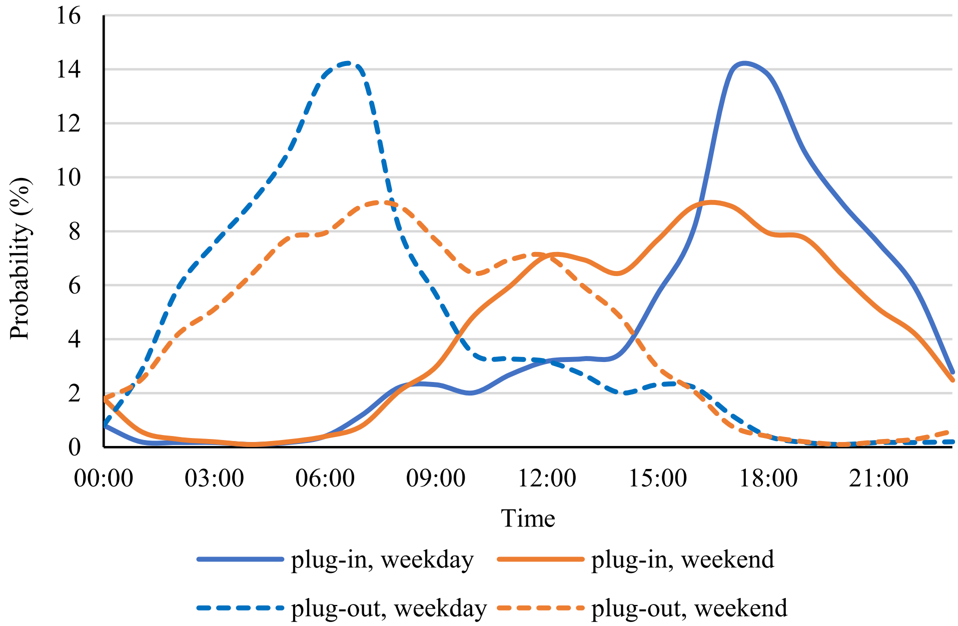


**Fig. 2.** Plug-in/out time profile (Plug-in times from [34]. Plug-out times adopt midday mirrored approach, described in text, below).

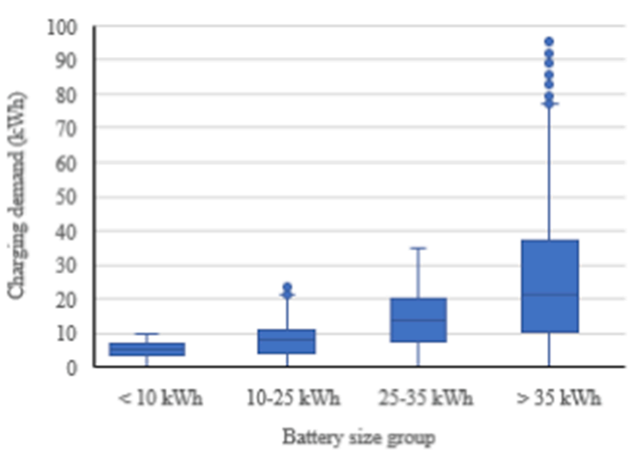


**Fig. 3.** Electric Nation trial - average charging demand per session (Data from [33]).

charging depending on each user's tariff, described as *scheduling* hereafter. The output of the scheduling is the energy transferred to each EV at each time step, here set to 30 min. At each iteration, the scheduling algorithm is implemented over the scheduling window which is smaller than the total simulation period.

In the implementation described here, the scheduling window is set to one week, starting from 12 PM on Monday to 12 PM the following Monday. If a car remains connected over two sequential scheduling windows, it is assumed that the car disconnects as the first window ends at 12 PM and immediately reconnects at the start of the next scheduling window. Any energy shortfall from the first window is rescheduled into the next scheduling window. To do this, another session for this car is generated with plug-in time on 12 PM Monday and the plug-out time as for the original plug-out time. 12 PM was chosen for the start of scheduling windows as fewer cars are typically connected at midday, reducing the number of sessions interrupted in this way.

In each scheduling window the scheduling algorithm, depicted in Fig. 4, iterates over all tariffs in set $C$. If at least one user uses a tariff as its criteria for smart charging, that tariff is included in $C$. $C_k \varepsilon C$ is a matrix with two columns: time stamp, $t$, and the tariff of that time stamp, $c$. This matrix is sorted by tariff in ascending order. The time with minimum tariff is selected and all the EVs that are connected at that time and use this tariff ($EV_{ti}$) are considered to be charged at this time stamp. Their remaining demand is then updated accordingly. In the next iteration, the next time with the second smallest tariff is selected and all EVs that are connected at that time and use this tariff are charged. This continues until all EVs receive their energy demand.

The subroutine shown to the right of the main column in Fig. 4 is only implemented when capacity-managed charging is applied. In this case, at each time stamp, the total load from charging EVs in sum($P_{EVti}$) is compared with the spare headroom of the transformer at that time stamp, $h_t$. The spare headroom at each time is the transformer rating in kW minus the non-EV load at that time. If the load exceeds the spare headroom, some EVs need to be removed from $EV_{ti}$. The EVs in $EV_{ti}$ are prioritized based on their connection time in the current session. Those with shorter connection times are given higher priority. Excluded EVs are removed from $EV_{ti}$ until sum($P_{EVti}$) is smaller or equal to $h_t$. If remaining capacity is less than the maximum charger rate of the next EV with the highest priority, that EV will be charged at a reduced rate up to the spare capacity of the transformer; otherwise, all EVs are charged at maximum speed.

### 2.3.3. Loads and average loads formulation

Half-hourly load profiles averaged across each simulation period are presented amongst results below, to enable ready comparison between simulations. The analysis combines dynamic half hourly values for simulated EV load with a static profile to represent established non-EV load. Eqn. (1), (2) and (3) detail the average load calculation for each of the 48 time stamps for all days, weekdays and weekends respectively. The total load at any time stamp is the sum of EV load and non-EV load in that time stamp (Eq (4)).

$$\overline{P}_{ki} = \frac{\sum_{d=1}^{n\_days} P_{kdi}}{n\_days}, \ k \in [EV, nonEV, total], \ i \in [1, 48], \ d \in [1, n\_days] \tag{1}$$

$$\overline{P}_{ki}^{wkdays} = \frac{\sum_{d=1}^{n\_wkdays} P_{kdi}}{n\_wkday}, k \in [EV, nonEV, total], i \in [1, 48], d \in [1, n\_wkdays] \tag{2}$$

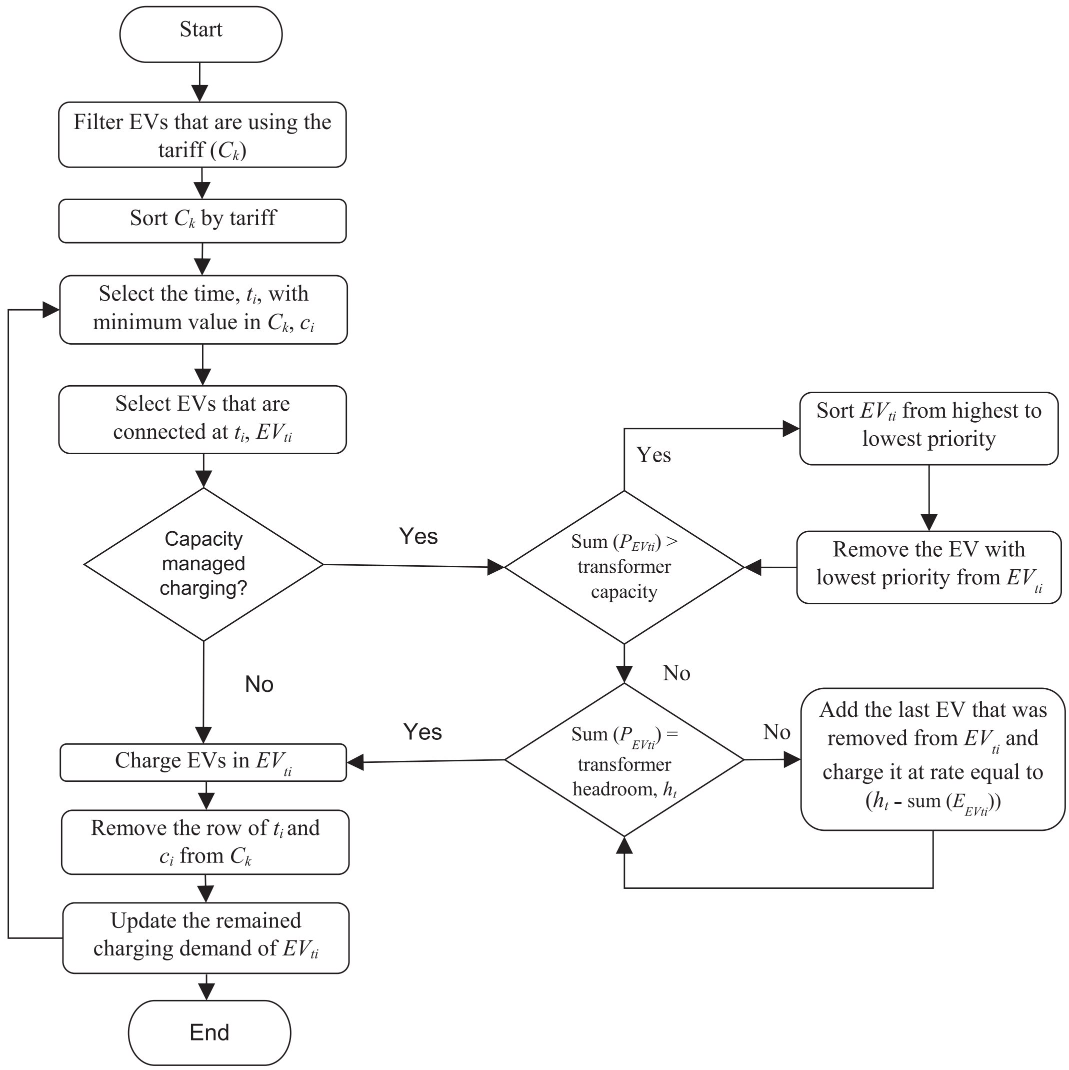


**Fig. 4.** The scheduling algorithm.

$$\overline{P}_{ki}^{wkends} = \frac{\sum_{d=1}^{n\_wkend} P_{kdi}}{n\_wkend}, k \in [EV, nonEV, total], i \in [1, 48], d \in [1, n\_wkends] \quad (3)$$

$$P_{total,d,i} = P_{EV,d,i} + P_{nonEV,d,i} \quad (4)$$

*d:* index for days.
*i:* index for time stamps in a day, 1–48.
*k:* index for *EV, non-EV*, or *total*.
*P:* load (kW).
*n_days*: number of days of the simulation period.
*n_wkdays*: number of weekdays of the simulation period.
*n_wkends*: number of weekends of the simulation period.
$\overline{P}_{ki}$: Average EV, non-EV, or total load (kW) in *n_days*, at time stamp *i*, *i* ∊ [1, 48].
$\overline{P}_{ki}^{wkdays}$: Average EV, non-EV, or total load (kW) in *n_wkdays*, at time stamp *i*, *i* ∊ [1, 48].
$\overline{P}_{ki}^{wkends}$: Average EV, non-EV, or total load (kW) in *n_wkend*, at time stamp *i*, *i* ∊ [1, 48].

Although a useful indicator, average loads at each time stamp are not sufficient to effectively describe network stress. Therefore, other measures have been introduced to reflect the length of time that the grid is under stress as well as its severity. Transformers can tolerate a load somewhat above their nameplate capacity for a certain time and yet even a short period of overload can be problematic if far beyond the level of tolerance. There are various standards based on the type of transformer and weather conditions. For instance, the primary transformer application and rating policy (TRAN-01–004) states that ONAN[1] transformers can have a generic cyclic overload up to 130% for 3 h. For the remaining hours in a 24-hour period, the load of the transformer should be 80% or less of the rated capacity to allow the transformer to cool down [35]. WPD's Standard Technique TP4B/2 states that when selecting fuses for 11 kV and 6.6 kV transformers, "Transformer overloads up to 150% of nameplate rating shall be possible" [36].

Overload at any time stamp is taken as the difference between the total load at that time and the capacity. If the total load is less than the capacity, the overload is zero (Eq (5)). The percentage of exceedance incidents is defined by the number of time stamps when exceedance happens (Eq (6)), divided by the total number of time stamps in the entire simulation period (Eq (7)). The severity of the stress is taken as the average of the load divided by the capacity of the substation, only when the load on the transformer is higher than its capacity (Eq (8)).

$$P\_over_{di} = min(0, cap - P_{total,d,i}) \quad (5)$$

$$n\_over = count(P\_over_{di} | where P\_over_{di} > 0) \quad (6)$$

[1] Oil Natural Air Natural.

$$\%n\_over = \frac{n\_over}{n\_HH} \times 100 \tag{7}$$

$$\overline{P\_over\_pos} = \frac{\frac{\sum_{d=1}^{n\_days}\sum_{i=1}^{48}(P_{total,d,i}|P_{total,d,i}>cap)}{n\_over}}{cap} \times 100 \tag{8}$$

$$\overline{Peak} = \frac{\sum_{d=1}^{n_{days}} Max(P_{total,i}), i \in [1, 48]}{n_{days}} \tag{9}$$

$P\_over_{di}$: overload at day $d$ and time stamp $i$.

*n_over:* the number of time stamps with overload.

*%n_over:* overload percentage.

$\overline{P\_over\_pos}$: Average overload percentage when overload is greater than zero.

*cap*: The capacity of substation.

*n_HH*: the number of half hours in the entire simulation period.

## 3. Results

The following results are drawn from model runs examining secondary substation level only, with an assumed 384 houses connected through low voltage feeders. Each house is taken to have no more than one EV and dedicated charger.

### 3.1. Smart charging – Assessing peak load impact with increasing EV penetration levels.

Simulations were run with EV penetration varying from zero to 100% in 5% increments, for each of the tariffs. The results are shown as box plots in Fig. 5, representing 50 model runs for each penetration / tariff combination. Each data point shows the percentage increase in the 30 day average half hourly domestic peak due to the additional charging demand calculated by subtracting the non EV load at each time period from the total with EV load (Eq (9)).

The increase in peak load varies substantially by tariff, with the average increase ranging from 7% to 97% above the non EV peak for 50% EV penetration. In on-demand charging, the increase in peak is a linear function of EV penetration. In this case, plug-in times tend to coincide with peaks in non-EV load in the evening and any increase in EV penetration increases the peak load. Except at very low penetrations (15% or below), the DUoS based tariff leads to a notably greater increase in peak than the on-demand case. A similar trend is seen with the Economy7 tariff, albeit lower and only exceeding on-demand for penetrations above 35%. These two *step-wise* tariffs present the greatest impact for the distribution grid even at modest EV penetrations. This can be explained through a combination of the tariff structure and user behaviour. Both tariffs drop price at a fixed time in the evening / overnight when a large share of vehicles are back at home, connected and awaiting charge.

By contrast, the dynamic tariffs (dynamic price and carbon intensity) lead to much less stress on the grid than the stepwise tariffs. Up to 40% EV penetration, these tariffs do not give rise to any increase in peak as all additional load is accommodated at off-peak times when electricity price is lower. As EV penetration is increased above 40%, these tariffs gradually give rise to a new peak load, with combined demand at lower price time slots beginning to exceed the traditional non-EV evening peak. This result is a feature of applying dynamic prices without grid constraints or any price feedback, discussed further in section 4.

The combination of tariffs selected for the balanced case appear the most sympathetic in terms of network stress. Although some increase in peak demand is seen for all stages of EV uptake, this remains at a low level and is the least of all the cases tested for EV penetrations above 55%. This increase in peak is still concerning, however, rising above 50% of the non-EV peak with 100% EV uptake.

### 3.2. Smart charging - impact on load profile

To further explain the increases in peak load seen above, this section examines average half-hourly load at discrete time steps, set against an assumed secondary substation capacity threshold. Attention is given to cases with 40% EV penetration. This represents the highest level, as seen in Fig. 5, where EVs can be introduced following dynamic tariffs without an increase in the half-hourly average peak. At such levels, only the DUoS informed tariff shows an increase in peak greater than on-demand charging. An indicative headroom capacity of 30% is selected, being the headroom needed to accommodate the half hourly average peak resulting from on-demand charging at 40% EV penetration. The output is shown in Fig. 6, including the average EV and average non-EV load at half-hourly time stamp $i \in [1, 48]$ for all days of simulation, $\overline{P}_{ki}$, for weekdays $\overline{P}_{ki}^{wkdays}$, and weekends $\overline{P}_{ki}^{wkends}$ during the entire simulation period.

As noted above, the shape of the load profile is influenced by the users' choices of plug-in times in combination with the tariff's price-time function. This produces some widely varied results:

- With on demand charging the additional load adds directly to the evening non-EV peak with many vehicles arriving home and

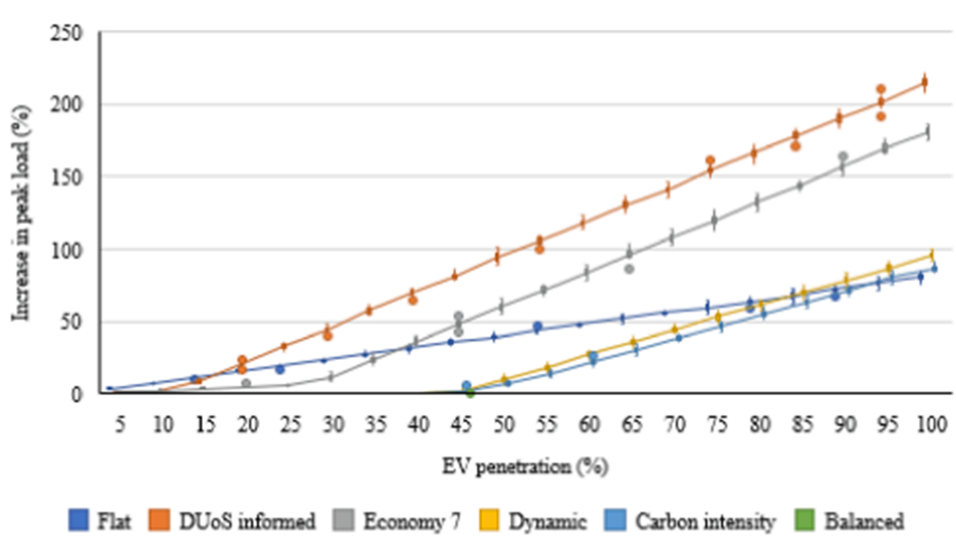


**Fig. 5.** Increase in domestic peak demand (shown as % of non EV peak) with EV adoption level.

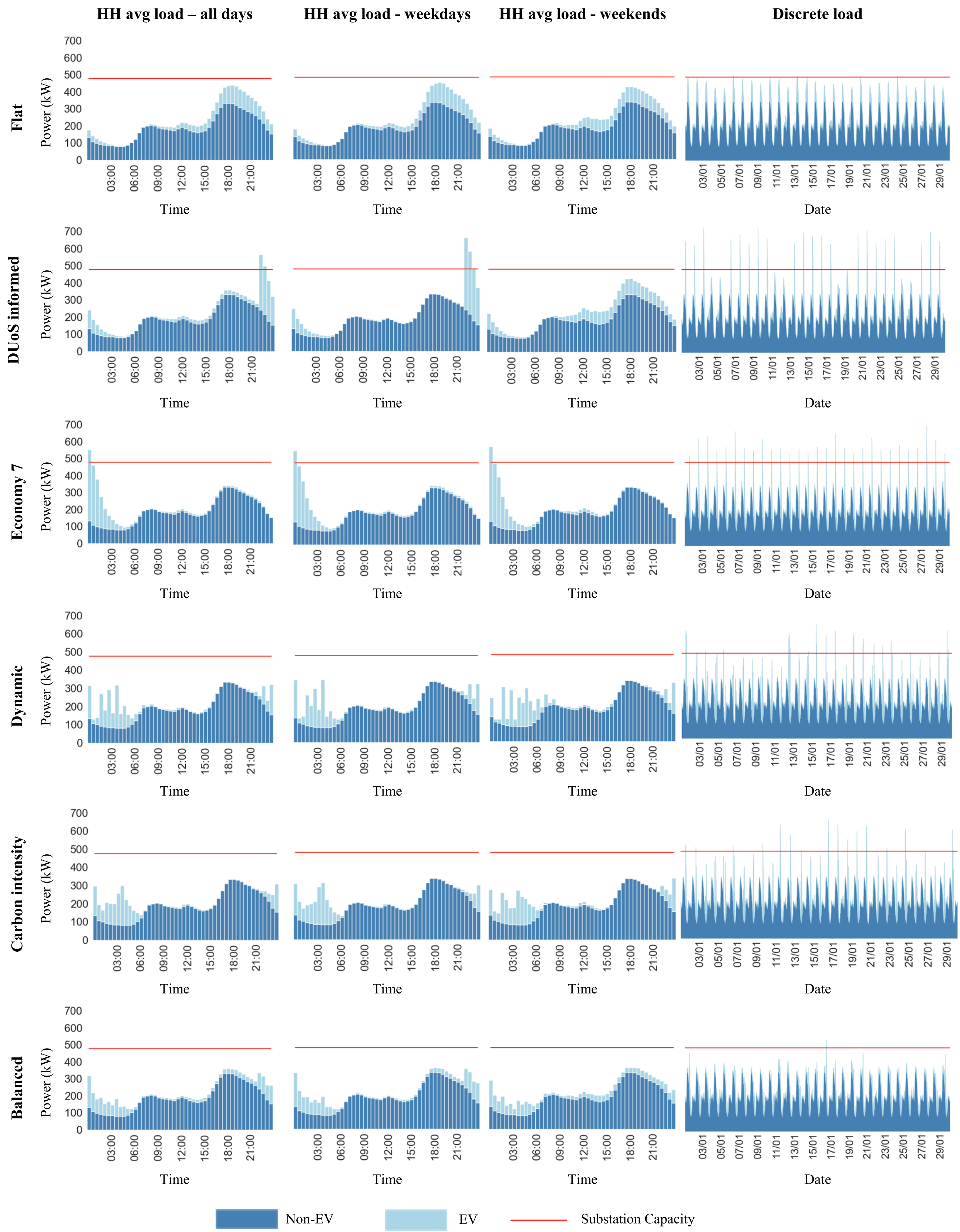


**Fig. 6.** Half-hourly load with various tariff / smart charging assumptions, 40% EV penetration. First three columns show HH load averaged across all days, weekdays and weekends respectively. Final column shows discrete loads at all time steps.

plugging in across this period. This effect is smaller at weekends with plugin times spread more evenly across the day.

- With the DUoS informed tariff, prices drop at 8:30 PM on weekdays, leading to an instantaneous pickup for all EVs that are connected and awaiting charge at that time. As a high share of EVs are connected by this time, this creates a very sharp load increase. Over weekends the price structure is flat so load profile is identical to the on-demand case.
- Economy 7 prices drop at midnight, leading to a sharp increase similar to T2 only somewhat later in the overnight period.
- With both the dynamic price and carbon intensity tariffs, sharp peaks in the average profile are avoided with most charging happening between midnight and 6 AM.
- In the balanced case, people use different tariffs and objectives for charging. This creates more diversity in selecting the best time slots for charging and decreases the overloads and stress on the grid.

The fourth column of subplots in Fig. 6 shows the discrete half hourly load for all time steps across the 30 day analysis period. This reveals a very different picture. Having selected a capacity threshold which is acceptable for the on-demand case it is seen that all other single tariffs show multiple overload events, some of which are of significant magnitude. Only the case with a combination of tariffs performs better than on-demand from this standpoint. Closer attention is given below to quantifying these events.

### 3.3. Smart charging – Assessing overload

Section 2.3.3 noted a diversity of approaches in quantifying transformer overload and defined four relevant metrics. These metrics have been recorded from a set of 1000 model runs for each tariff combination at 40% and 100% penetration levels. Results are illustrated as box plots in Fig. 7 alongside average loading.

Differences are seen when stepping from 40% to 100% EV

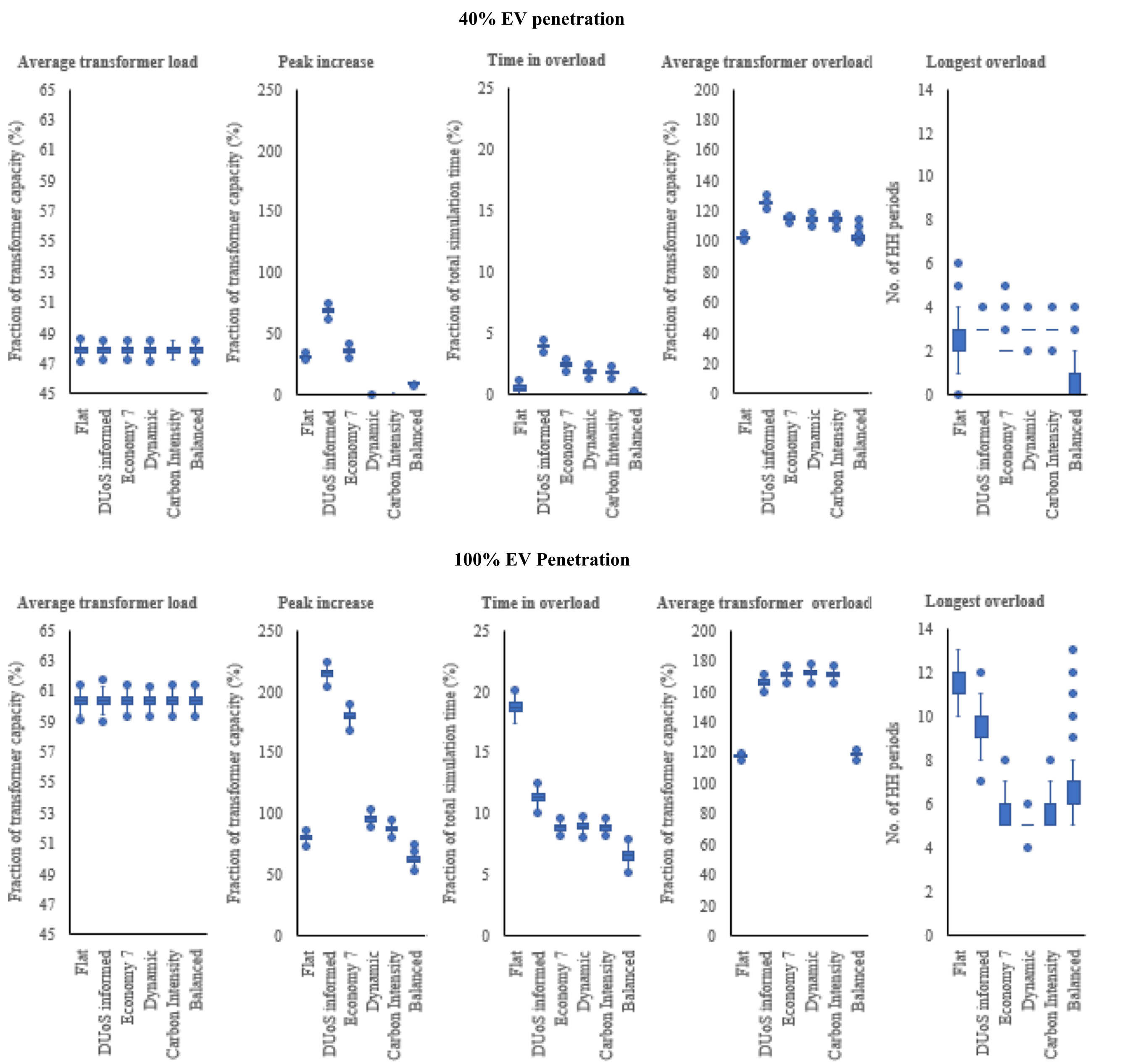


**Fig. 7.** Overload statistics for 40% and 100% EV penetration for the six tariff schemes. Boxes indicate quartiles, while whiskers show full variability excluding outliers identified as separate points.

penetration, with the on-demand case now resulting in the greatest number of overloads. The length of overloads increases across all tariff cases while remaining highest for the on-demand case. Again the combination case remains the most benign, yet even this case shows some lengthy overload events.

### 3.4. Carbon emissions

Carbon emissions attributed to grid electricity for charging the vehicles are presented in Fig. 8. From this perspective, all smart tariffs deliver a considerable improvement over uncontrolled charging. Of the stepwise tariffs, Economy 7 results in much lower carbon emissions than a DUoS informed option, reflecting reduced carbon intensity during the later overnight periods. Dynamic tariffs tend to reduce emissions further, with the dynamic price based tariff leading to emissions close to the tariff that seeks the very lowest carbon periods.

### 3.5. Capacity-managed charging

From the results above it was seen that none of the plausible smart charging tariffs (or combination) was successful in completely avoiding an increase in peak demand, with some element of overload seen in each case, even at just 40% penetration. This raises the question whether alternative control strategies would be more effective at protecting the local network. To test for this, an algorithm was implemented which sought to reschedule all load away from the peak period. Each tariff case was simulated with 100% EV penetration. The average half-hourly loads in all days, weekdays, and weekends as well as the individual loads versus transformer capacity are presented in Fig. 9.

With 30% headroom assumed, as above, the capacity managed approach was seen to successfully deliver the required energy in most cases, with an almost negligible level of unserved demand in some model runs. A sample of 10 model runs were examined in detail, revealing no unserved demand in 6 of the runs and no more than 2 car charging sessions, out of 7376, being affected in each of the other runs. These tended to be small levels of under-delivery for large session charging requirements, at most a 7kWh shortfall from a 73.5kWh requirement.

Under this capacity managed regime, the influence of the individual

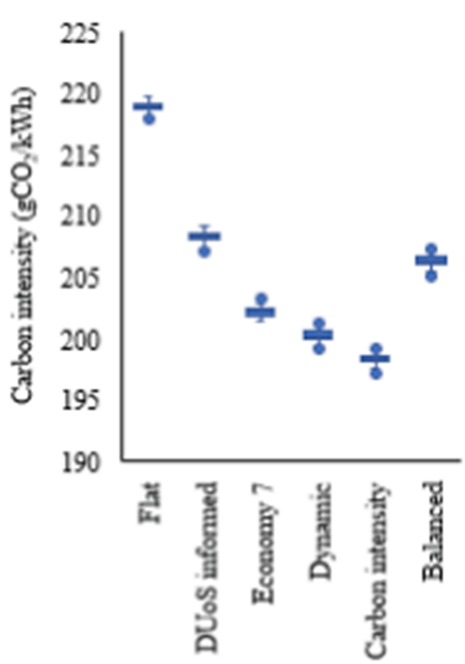


**Fig. 8.** Comparative carbon emissions per unit of charge for the five tariff options.

tariffs on the average profile remains notable. On-demand charging leads to an extended period, in the early evening, where transformer capacity is saturated. Although within the assigned limit, such extended high demand still risks damage to network infrastructure. Similarly, step-wise tariffs also lead to periods of saturated capacity, beginning in the late evening for the DUoS informed tariff and after midnight for Economy 7. The dynamic tariffs give rise to less regular periods of maximum load, with the average profiles showing some headroom remaining at all time periods.

## 4. Discussion

The heterogeneity of EV users and their diverse requirements for charging have been widely discussed in the literature. Different user typologies (e.g. commuter/non-commuter, income level, etc.) lead to a range of charging requirements in terms of plugin / out times and energy demand which are important factors in understanding the aggregate charging load. The results above show the need to consider specific tariffs in combination with user requirements when assessing the impact of EV charging, considered in terms of load profile as well as peak demand and the frequency and size of overloads.

The results have shown substantive differences in the EV charging load profiles that result from the interplay between a range of tariff design and behavioural choices. Some stochastic variation was applied to user actions, notably connection time and state of charge; however the governing probabilities were drawn from a single user study – the Electric Nation trial. This trial reflects a particular moment in time in terms of vehicle battery size (and subsequently ranges) and plausibly some self-selection bias from the early adopters choosing to participate. Nonetheless, a wide spread in plug-in times and energy needed per charge leads to a lower grid impact from on-demand charging than suggested by some earlier studies. Rather than explicitly examining user behaviours, the model runs described above were designed to explore the impact of a range of plausible tariff designs, with automated design response. Tariff choice was seen to have a very significant impact on the aggregate load profile, with certain tariff choices leading to grid overloads that are potentially worse than the "flat" on-demand case.

The impact of different tariffs was seen to vary with the EV penetration level assumed. At low penetrations (<15%) the uncontrolled tariff makes a small impact to peak load, by directly increasing the evening peak (see Fig. 5). However, at penetrations above this, stepwise tariffs lead to a higher overnight peak which begins to dominate. At very high penetrations (greater than 80%), even the fully dynamic tariffs lead to a new peak that is higher than the uncontrolled case. This arises as these tariffs exhibit a single cheapest half-hour period which attracts whatever demand possible, considered further below. At modest (40%) penetration, the DUoS informed tariff gives rise to the largest number of overload events and the highest percentage increase in peak. In turn, with 100% EV penetration the uncontrolled tariff leads to the highest number of overloads.

Stepwise tariffs are seen to have the potential to be particularly problematic. This concern has been recognized for some time. In the UK, Economy 7 and similar tariffs lead to a small but notable demand peak after midnight. However, in this study we see that the combination of overnight cheap periods with the predominance of cars being connected and available to charge at this time exacerbates the impact. This contrasts with the smoothing to on-demand charging that comes from staggered evening homecoming. The combination of user behaviour and tariff design is critical here.

In noting concerns with dynamic tariffs it must be stressed that this study does not incorporate price feedback. Results with EV penetrations over 85% have shown new demand peaks occurring, due to time shifted EV charging, which exceed the previous non-EV evening peak. This would be unlikely were demand feeding back effectively to price. As the level of load seeking low prices increases it might be expected that increased demand at any given time would lead to a simultaneous price

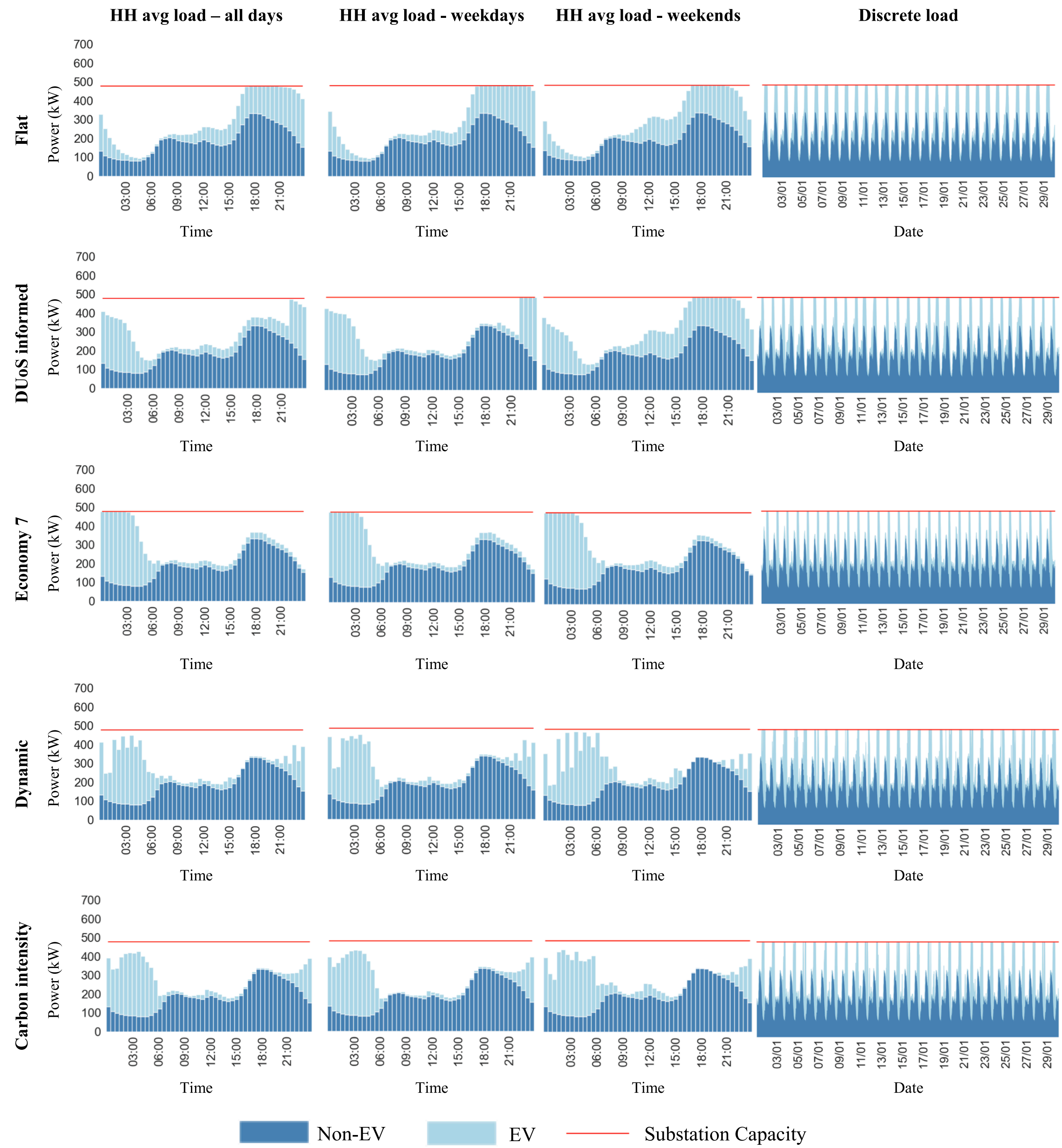


**Fig. 9.** Half-hourly load with various tariffs combined with capacity-managed charging, 100% EV penetration. First three columns show HH load averaged across all days, weekdays and weekends respectively. Final column shows discrete loads at all time steps.

increase and a smoothing effect would occur, reducing the level of demand shifted. However, in the current market, dynamic tariffs follow wholesale prices which emerge nationally so such smoothing would only occur when national EV penetrations reach high levels. This raises the question whether EV uptake will cluster spatially such that excessive local penetrations would be seen before national price smoothing occurs and, if so, how high might such local penetrations reach. This would seem most likely to occur at the lowest network tier first (secondary substation level). Further research to examine this potential and effective monitoring of EV uptake would be recommended. Some element of local pricing could mitigate this risk, though true local, dynamic pricing might be seen as excessively complex and potentially inequitable.

Single tariff cases, where all users adopt the same tariff, lead to the most extreme load characteristics seen, whereas the combined case appears less challenging for grid operation. It would be hoped that widespread adoption of a single tariff would be avoided in an effective, diversified market. However, there is a risk that local factors, such as neighbourhood cooperation, targeted marketing or local authority support could lead to a single scheme being adopted intensively in one area. There is also a risk that multiple tariffs could be driven by a single, synchronizing factor such as the wholesale price or the DUoS pricing scheme. Such effects could present a network risk, which again suggests a need to understand tariff adoption with high spatial granularity.

By contrast with metrics of grid stress, all smart tariffs present an improvement in carbon emissions, with a true dynamic price closest to a tariff that tracks carbon intensity directly. The most striking difference is seen with the two step-wise tariffs. With consistently low overnight carbon intensity due to reduced demand, a traditional Economy 7 approach leads to a much greater reduction in carbon emissions than a tariff that simply seeks to avoid the evening peak as represented by DUoS charging bands. Energy suppliers have begun to offer a variety of EV specific tariffs, many of which are simple step-wise tariffs to avoid the complexity of true dynamic pricing. The results suggest that significant carbon benefit could be realized by ensuring such tariffs actively target low carbon times, rather than just avoiding the time of most extreme peak demand. In the longer term, as with the potential for price feedback, high levels of demand response can be expected to change the pattern of carbon intensity. This potential is of strong interest for future research, together with the competing response between EV charging and other demand sectors.

The approach implemented has sought to distinguish between the influence of smart charging, following plausible commercial tariffs (which would likely be influenced by wholesale prices and national scale factors) from a separate capacity management strategy to control any unacceptable demand peak which could arise from local clustering of EV adoption. Certain tariffs were seen to help mitigate the peak but these do not offer a perfect solution. Meanwhile a strategy to deliberately allocate charging away from any overload showed that it was possible to serve all required charging demand in most cases with unserved demand negligible even in the rare model runs where it occurred.

Although unserved demand resulting from capacity management was negligible, given the 30% headroom assumption, the implementation process raised some challenges. We were not able to define a single, inherently fair approach to share any unserved demand which should arise. Any approach adopted essentially represents a human judgement and could be seen as unfair by some participants. There is potential for complexity in markets such as the UK where a multitude of actors could have a role in such decision making. Control actions implemented by a network operator might differ from those enacted by charge control management companies acting on a commercial basis. Expectations around visibility to the end user and approach to cost / benefit sharing need scrutiny as stakeholder responsibilities and commercial offerings evolve.

The analysis presented above concentrates specifically on flexible load from charging EVs, while non-EV load is treated as a fixed, static profile. There are numerous opportunities to shift electricity demand for other services, especially with demand growth anticipated from heat electrification. This could bring a comparable risk that other flexible demand also grows unevenly in certain localities and amplifies concerns raised by this paper. The framework described can be readily extended to address flexibility in non-EV loads and the authors are actively seeking opportunities to progress research with this in mind.

## 5. Conclusions

We have presented a charging dispatch model, developed to assess the impact of smart EV charging to the power grid under various tariff designs and multiple vehicle adoption levels. The work has covered a wider range of tariffs than previous studies, while examining the separate implementation of a capacity management strategy and assessing the power grid carbon emissions from each scenario. Insights have been gained regarding the risks and benefits from certain tariff designs, the change in these risks with increased EV adoption and the need to ensure a diversity of tariffs are adopted.

Stepwise tariffs presented the greatest threat of grid overload, leading to greater peaks at different times to established non-EV peak loads. On-demand charging can lead to longer and more frequent overloads, though staggered homecoming of Electric Nation participants limited the increase in peak demand seen. A combination of tariffs reduced the grid impact well below that of any single tariff. Regulatory intervention may be required to avoid mass adoption of single tariffs or over-similar tariffs.

All smart tariffs result in a reduction in charging related carbon emissions from the electricity grid, with the greatest saving seen from a true dynamic tariff. A stepwise tariff which specifically targets low carbon time periods has potential to deliver notably greater savings than one that just avoids peak demand. This has clear implications for the design of EV tariffs, with many energy suppliers currently favouring stepwise offerings.

At higher EV adoption levels, smart charging under market-based tariffs fails to avoid peak load increase. By contrast, targeted capacity management was able to eliminate overload even at very high EV uptake levels, with only rare, very small levels of unserved demand (given 30% non-EV headroom at secondary substation level). Such active control measures could become necessary for network operators if clusters of high local EV penetrations occur ahead of national EV adoption. Care would be needed to ensure a small number of end users do not face an unfair burden if such actions are implemented.

## CRediT authorship contribution statement

**Farzaneh Daneshzand:** Investigation, Visualization, Writing – original draft. **Phil J. Coker:** Conceptualization, Writing – review & editing. **Ben Potter:** Conceptualization, Project administration. **Stefan T Smith:** 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. [Ben Potter reports a relationship with CrowdCharge Ltd that includes: employment].

## Data availability

Code created in undertaking this research has been made available as an open source resource, available at https://doi.org/10.17864/1947.000444

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## References

[1] Muratori M. Impact of uncoordinated plug-in electric vehicle charging on residential power demand. Nat Energy 2018;3(3):193–201.
[2] Crozier C, Morstyn T, McCulloch M. Capturing diversity in electric vehicle charging behaviour for network capacity estimation. Transp Res D 2021;93:102762.
[3] Neaimeh M, Wardle R, Jenkins AM, Yi J, Hill G, Lyons PF, et al. A probabilistic approach to combining smart meter and electric vehicle charging data to investigate distribution network impacts. Appl Energy 2015;157:688–98.
[4] Gerritsma MK, AlSkaif T, Fidder H, van Sark W. Flexibility of electric vehicle demand: analysis of measured charging data and simulation for the future. World Electr Veh J 2019;10(1):14.
[5] UK Gov. Electric Vehicles (Smart Charge Points) Regulations 2021. UK Government; 2021.
[6] Aravinthan V, Jewell W. Controlled electric vehicle charging for mitigating impacts on distribution assets. IEEE Trans Smart Grid 2015;6(2):999–1009.
[7] Crozier C, Morstyn T, McCulloch M. The opportunity for smart charging to mitigate the impact of electric vehicles on transmission and distribution systems. Appl Energy 2020;268:114973.
[8] Venegas FG, Petit M, Perez Y. Plug-in behavior of electric vehicles users: insights from a large-scale trial and impacts for grid integration studies. eTransportation 2021;10:100131.
[9] Kucuksari S, Erdogan N. EV Specific Time-of-use Rates Analysis for Workplace Charging. In: IEE Transportation Electrification Conference & Expo (ITEC); 2021.

[10] Kütt L, Saarijärvi E, Lehtonen M, Rosin A, Mõlder H. Load Shifting in the Existing Distribution Network and Perspective for EV Charging-Case Study. In: 5th IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe), October 12-15, Istanbul; 2014.
[11] Veldman E, Verzijlbergh RA. Distribution grid impacts of smart electric vehicle charging from different perspectives. IEEE Trans Smart Grid 2015;6:333–42.
[12] Powell S, Kara EC, Sevlian R, Cezar GV, Kiliccote S, Rajagopal R. Controlled workplace charging of electric vehicles: the impact of rate schedules on transformer aging. Appl Energy 2020;276:115352.
[13] Pimm AJ, Cockerill TT, Taylor PG. Time-of-use and time-of-export tariffs for home batteries: effects on low voltage distribution networks. J Storage Mater 2019;18:447–58.
[14] F. Salah, J. P. Ilg, C. M. Flath and C. v. Dinther, "Impact of electric vehicles on distribution substations: A Swiss case study," *Applied Energy,* vol. 137, pp. 88-96, 2015.
[15] UK Gov. UK Government GHG Conversion Factors for Company Reporting; 2021. [Online]. Available: https://www.gov.uk/government/collections/government-conversion-factors-for-company-reporting. [Accessed 11 May 2022].
[16] Khan I, Jack M, Stephenson J. Analysis of greenhouse gas emissions. J Clean Prod 2018;184:1091–101.
[17] Chen S, Guo Z, Liu P, Li Z. Advances in clean and low-carbon power generation planning. Comput Chem Eng 2018;116:296–305.
[18] Hitchin E, Pout C. The carbon intensity of electricity: How many kgC per kWhe? Building Services 2002;23(4):215–22.
[19] Hawkes A. Long-run marginal CO2 emissions factors in national electricity systems. Appl Energy 2014;125:197–205.
[20] National Grid ESO. Carbon Intensity Web Portal; 2022. [Online]. Available: carbonintensity.org. [Accessed 11 May 2022].
[21] Daneshzand F. EV Smart Charging simulation and dispatch – code and configuration data; 2023. Software. https://doi.org/10.17864/1947.000444.
[22] UK Gov. Government takes historic step towards net-zero with end of sale of new petrol and diesel cars by 2030; 2020. [Online]. Available: https://www.gov.uk/government/news/government-takes-historic-step-towards-net-zero-with-end-of-sale-of-new-petrol-and-diesel-cars-by-2030. [Accessed 06 2022].
[23] UK Gov. Decarbonising Transport, A Better, Greener Britain, Department for Transport; 2021.
[24] Western Power Distribution, Electric Nation, Formerly CarConnect. Project details; 2019. [Online]. Available: https://www.westernpower.co.uk/innovation/projects/electric-nation.
[25] Western Power Distribution, Electric Nation. Customer trial website; 2019. [Online]. Available: https://electricnation.org.uk/resources/smart-charging-project/. [Accessed 10 01 2021].
[26] SSEN. Southern Electric Power Distribution plc. Use of System Charging Statement; 2019. [Online]. Available: https://distribution.ssen.co.uk/Library/ChargingStatements/SEPD/.
[27] Energy-stats.uk, 2021. [Online]. Available: https://www.energy-stats.uk/download-historical-pricing-data/. [Accessed 03 08 2022].
[28] USwitch, EV Energy Tariffs; 2022. [Online]. Available: https://www.uswitch.com/electric-car/ev-energy-tariffs/. [Accessed 1 September 2022].
[29] National Grid ESO. Historic Generation Mix & Carbon Intensity; 2021. [Online]. Available: https://data.nationalgrideso.com/carbon-intensity1/historic-generation-mix. [Accessed 13 August 2021].
[30] Elexon, Load Profiles and their use in Electricity Settlement; 2018. [Online]. Available: https://www.elexon.co.uk/documents/training-guidance/bsc-guidance-notes/load-profiles/.
[31] POST. Post Note 163. UK electricity networks. Parlimentary Office of Science and Technology; 2001.
[32] Papadopoulos P, Skarvelis-Kazakos S, Grau I, Cipcigan LM, Jenkins N. Impact of residential charging of electric vehicles on distribution networks, a probabilistic approach. In: IEEE vehicle power and propulsion conference. France: Lille; 2010.
[33] Western Power Distribution, Project data portal; 2019. [Online]. Available: https://www.westernpower.co.uk/project-data.
[34] Western Power Distribution, Electric Nation. Customer Trial Final Report; 2019. [Online]. Available: https://electricnation.org.uk/resources/smart-charging-project/.
[35] SP Energy Networks. Enhanced Transformer Ratings Tool - A Design and Planning Application Guide. Report No: 7640–09–R0; 2015.
[36] Western Power Distribution. Standard Technique TP4B/2; 2001.