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Emissions from charging electric vehicles in the UK

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ABSTRACT

Understanding how to best integrate electric vehicles (EVs) into electricity systems is key to the success of both sectors. We pair national-scale EV charging data with high resolution electricity generation data for the UK to calculate the average and marginal emissions produced through charging EVs. Considering the average generation mix weighted by when charging occurs, a typical Battery EV (BEV) emitted 41 g CO_2, 27 mg NO_x and 0.7 mg $PM_{2.5}$ per kilometre in 2019. A static analysis using annual averages underestimates these values by 4 %. The 'marginal' emissions from BEV charging are 25 % higher than average emissions for CO_2 and NO_x, and 50 % lower for $PM_{2.5}$. Smart charging was found to reduce average CO_2 emissions by 10 % when compared to the typically charged vehicle; however, smart charging strategies may increase marginal emissions. Future smart charging strategies should minimise marginal emissions and will require access to 24-hour opportunistic smart charging.

1. Introduction

In many decarbonising economies the transportation sector is an important source of greenhouse gases and air pollutants (Friedlingstein et al., 2020). The recent progress and rollout of passenger car Battery EVs (BEVs) may bring the success of decarbonising the electricity sector to the transport sector. This critical link between sectors and technologies must be well understood for both to function as desired, and to avoid shifting the emissions problem elsewhere. This link consists of how BEVs are charged and the resulting impact on the electricity system. In this study we determine the historical air pollutant and greenhouse gas emissions produced from generating electricity for BEV charging and how different ways to measure these emissions and to charge BEVs would have altered emissions.

There is still controversy over whether BEVs truly reduce greenhouse gas emissions relative to conventional ICE vehicles, in part due to the electricity generation needed to charge them (Paton, 2020; Sternberg et al., 2019). Although such claims are widely refuted, increasingly via multi-national studies (Hoekstra, 2019; Knobloch et al., 2020), these typically focus on a single pollutant (CO_2) and the annual-average electricity generation mix. The true consequential emissions of charging an EV is complicated by the time-varying nature of electricity generation (Tranberg et al., 2019), and opacity over which specific generating technologies would meet the additional load to charge EVs (Ryan et al., 2016). Both aspects are the subject of this analysis.

The prospect of BEVs improving air quality through reducing exhaust emissions is not clear, mostly due to the contribution of non-exhaust $PM_{2.5}$ emissions to air quality in urban areas (Mehlig et al., 2021; Soret et al., 2014). BEVs displace exhaust emissions from the road to electricity generation emissions from power plants. To fully determine the impact of BEVs on air quality, these emissions released in power stations supplying BEV charging must be known. We determine these emissions in the UK for $PM_{2.5}$, NO_x, and SO_2 in

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this study.

Calculating the emissions resulting from charging BEVs therefore requires information describing both the electricity generation mix and how the vehicle was charged. Different methods are used for allocating emissions resulting from the generation of electricity supplying BEV charging, where the chosen method is specific to the aim of the research (Yang, 2013). From Yang (2013), these methods can be defined by three aspects of the approach: i) retrospective or prospective, ii) temporally constant or variable, and iii) average or marginal emissions.

These aspects are used below to frame three related research questions addressed in this paper:

i. *What emissions were produced in the generation of electricity for supplying BEV charging in the UK from 2010 to 2020?*
ii. *How does the time resolution of the method affect the emissions calculated?*
iii. *How have different BEV charging strategies change these emissions?*

The three key aspects of measuring emissions are discussed further in the following literature review sub-sections. Our methods are then followed by results which are structured around the research questions above. The discussion and conclusions consider how the methods and results from this paper inform the broader literature on BEV life cycle emissions.

2. Literature review

2.1. Retrospective or prospective

Prospective studies assess BEV technology in the future, using the present-day technology at present as a baseline, whereas studies of the present or past fall under the retrospective domain. Both retrospective and prospective methods rely upon a model of how a BEV is used. However, modelling BEVs and their charging has been challenging due to a lack of reliable empirical data and constraints resulting from limited vehicle range and charging infrastructure (Daina et al., 2017). This lack of data has limited retrospective studies until recently. As the number of BEVs on the road is growing rapidly, new resources of real-world empirical data describing their use are becoming available. Empirical data detailing the charging profile (the electricity demand over a 24-hour period of a BEV) can be combined with concurrent data of electricity generation, enabling the electricity generation emissions resulting from charging the fleet to be retrospectively determined. This method of pairing historical charging and electricity generation data was established by Robinson et al. (2013) and used more recently by Ensslen et al. (2017), where 7,704 and 29,262 charging events, respectively, were used to model how the BEVs were charged on average. These examples from the literature highlight the growing scale of charging data used to date. In this study, we use a previously-published national scale BEV charging dataset consisting of over 8 million charging events in the UK (Element Energy, 2019). We use their charging profile concurrently with high-resolution data of the UK's electricity generation, producing the first national-scale retrospective analysis to-date. This combination of data addresses the first research question: *What emissions were produced in the generation of electricity for supplying BEV charging in the UK from 2010 up to 2020?*

2.2. Temporally constant or variable

The final aspect of the modelling approach defines the temporal characteristic of the method. A temporally-constant method does not consider time-of-day variation within the period and uses the generation mix (and resulting AEF) averaged over the whole period. This AEF, typically taken for a single year, is then used to determine the emissions resulting from BEV charging. This approach is the most common (Marmiroli et al., 2018) as it does not require high-resolution data of the generation mix or the corresponding BEV charging profile; both of which can be difficult to obtain. Most LCAs and Well-To-Wheel studies use this approach (Marmiroli et al., 2018).

The alternative temporal method uses time varying data, allowing for short term variation of both electricity generation and BEV charging, as done in this study. The addition of high resolution data to this approach enables daily and seasonal variation of the electricity generation mix and different charging strategies to impact the resulting emissions. This difference has been quantified in the US, where a method which neglects the time of day the vehicle charges and the daily pattern of emission intensity was found to underestimate emissions by 11 % (Miller et al., 2020). The difference between these two temporal approaches has not been quantified for the UK. If this difference is significant, results in LCAs may be inaccurate as emissions from electricity generation is the most variable source of CO_2 across studies (Marmiroli et al., 2018). Here we fill this lack of understanding by answering: *How does the time resolution of the method affect the emissions calculated?*

2.3. Average or marginal emissions

The emissions produced from electricity generation to meet charging demand can be calculated using two methods: an average emission factor (AEF), or a marginal emission factor (MEF). Here, both AEF and MEF are used for all types of emission.

AEFs are used to quantify the real-time emissions of electricity generation. The AEF is the sum of all emissions produced by the fleet of power plants supplying electricity to grid in a given period, divided by the total net output of these power plants. Whereas MEFs are used to quantify the change in emissions resulting from a change in load on the system. A change in load is met by a change in output from a specific fleet of marginally-operating power plants. The change in emissions per unit change in load yields the MEF. The values of MEFs are typically different from AEFs as only a subset of power plants can respond to marginal changes in demand, whereas inflexible power plants (e.g. nuclear) or those which are weather-driven (e.g. wind and solar) do not.

The choice between using AEFs or MEFs depends on the temporal dynamics of the load on the electricity system for a retrospective analysis. AEFs are appropriate in retrospective studies where the load is viewed as static and unchangeable. Instead, if the load is additional or variable then MEFs are appropriate 3. In the short-run, demand from new BEVs will be an additional load on the system, and so warrants an MEF approach. Whereas for existing and consistent loads on the system, such as those from existing BEVs, an AEF approach is appropriate. There are many examples of both AEF-based studies (Faria et al., 2013; Foley et al., 2013; Rangaraju et al., 2015; Robinson et al., 2013) and MEF-based studies in the literature (Fang et al., 2018; Graff Zivin et al., 2014; Huber et al., 2021; Li et al., 2019; Tamayao et al., 2015; Yuksel et al., 2016). Both approaches are suitable depending upon the research question asked (Ryan et al., 2016). For example, Ensslen et al. (2017) use fixed charging load and AEF-based approach, as the study used empirical charging data based on vehicles without the ability to shift demand. Zivin et al. (2014) and Huber et al. (2020) instead use MEF-based approaches for determining the theoretical emissions of a BEV with a charging strategy that varies by time of day. Tamayao et al. (2015) use both approaches to highlight the how an MEF approach yields higher emissions in the US, noting that the MEF approach is the only appropriate method as BEV loads are always additional and variable to the system. Prospective studies undertaking scenario analysis have begun to include marginal emissions (Arvesen et al., 2021; Gai et al., 2019). Prospective studies require alternative methods for determining the AEF and MEF emissions produced due to a load on the future electricity system (Hawkes, 2014; Ryan et al., 2016), which are beyond the scope of this study. In this study we use both AEF and MEF approaches to illustrate how emissions from charging new and existing BEVs have changed over the past decade.

The concept of shifting BEV charging load to meet a desired objective is a well-covered topic in the literature (Ford, 1994; García-Villalobos et al., 2014). The simplest strategy to change charging behaviour is by switching to 'off-peak' charging. Off-peak charging delays the charge later into the evening when demand from other sources is lower, thus electricity is cheaper and typically of lower carbon content (in countries with relatively clean baseload electricity generation such as nuclear or hydro, such as the UK). To model an off-peak strategy we use an empirical charging profile taken from a recent large scale trial in the UK (Transport Research Laboratory, 2019). 'Smart charging' is a strategy which dynamically changes the charging profile to minimise a certain objective, such as cost to charge or the carbon content of the electricity. Two options are available for a retrospective analysis of smart charging using either: i) empirical data or ii) a simulation of smart charging. As no empirical data are currently publicly available in the detail or scale required for this study, a simulation of smart charging was used. With this, the third retrospective research question is: How have different BEV charging strategies changed charging emissions?

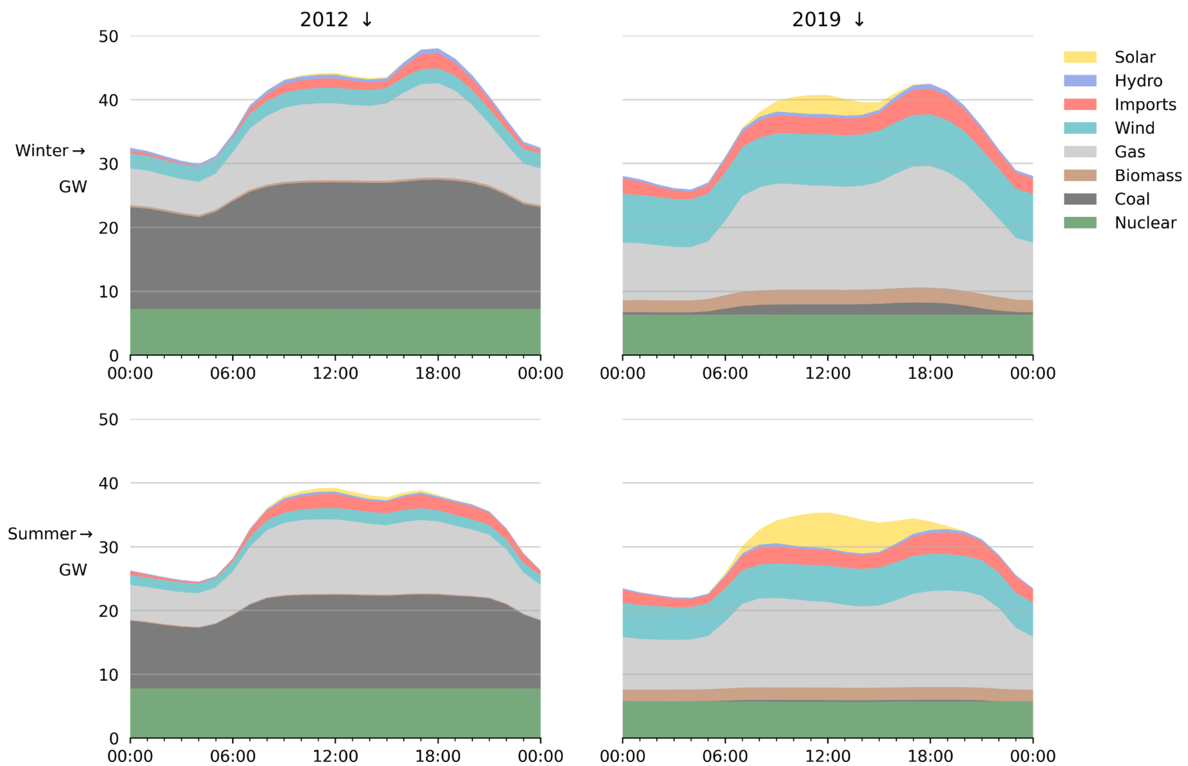

Fig. 1. Average daily electricity generation mix for the years 2012 and 2019 (left and right panels), and by season: winter and summer (higher and lower panels). This highlights three timescales for variability: diurnal, seasonal and interannual.

3. Methods

3.1. Electricity generation

Data on electricity generation in Great Britain was acquired using the methods given in Staffell (2017). These data contain the output of each power plant type, the carbon intensity of electricity generation, and further metrics, given at a 30-minute resolution from 2010 to the end of 2019. Fig. 1 uses this data to show the variability of Britain's generation mix over time.

3.2. Average emissions - AEFs

CO_2 emission factors for each power plant type are taken from Staffell (2017) and are given in the supplementary material. These emission factors were produced using historical data of the fuel consumption and efficiencies of the different generation power station types. These emission factors do not include upstream emissions resulting from the transportation of fuels or life-cycle emissions. This mirrors the system boundary we use for fossil-fuelled vehicles, where the emissions from combustion are included, but upstream emissions from oil extraction and refinery are excluded. An exception to this is biomass, where our emission factors encapsulate the supply chain which yields the fuel, whereas fuel consumption emissions in isolation are zero, as outlined in UNFCCC carbon accounting guidelines (UNFCCC, 2014).

Air pollutant emission factors for SO_2, NO_X, and $PM_{2.5}$ were derived from the National Atmospheric Emissions Inventory (NAEI, 2018). From the emission inventory for the year 2017, the total emissions of each power plant type were divided by the corresponding total output of the given generation type, yielding an emission factor for each. As with CO_2, these emission factors do not include upstream emissions (including biomass). The NAEI values for "wood combustion emissions from power plants" were allocated to biomass for this study as wood is the primary biomass fuel in the UK. Other studies have used significantly different air pollutant emission factors for biomass, revealing assumed emissions from biomass vary between countries and methods (Rangaraju et al., 2015).

A limitation of this method is the use of emission factors calculated for 2017 for all years. This may underestimate emissions before 2017 due the changing technology mix within power plant categories. The derived emission factors are given in the supplementary material. A second limitation is the use of single emission factors aggregated for each power plant type, which was necessary as the real-time output from individual power plants is not reported in the UK. This neglects the variation of emission rates between plants which may have different performance characteristics and operate differently, especially at the margin. However, the UK's fleet of plants were constructed in stages employing the same vintage of technologies (Ward et al., 2019), suggesting this limitation may not significantly affect the calculated emissions in this study.

3.3. Marginal emissions – MEFs

There are two options for calculating historical MEFs. The first is generation-based, where the known emission factors of individual generating units are used in a bottom-up approach to determine the emissions of the marginally-operating fleet of power plants. This

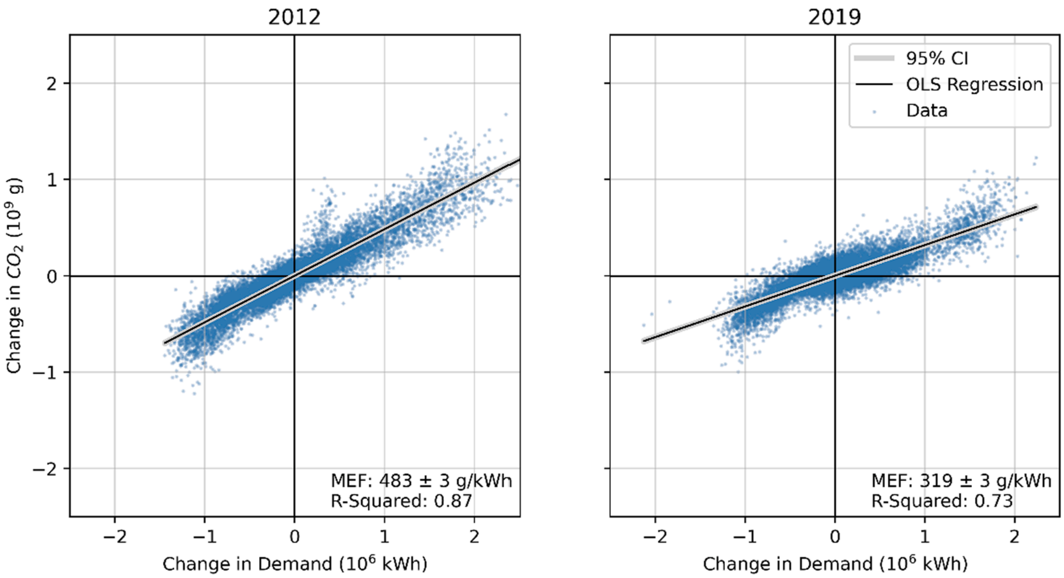

Fig. 2. Example calculation of the marginal emissions factor (MEF) for UK electricity generation in 2012 and 2019, using ordinary least squares (OLS) regression. The ± value in the legend and the shaded area around the regression line show the 95 % confidence intervals, which show uncertainty associated with the standard error.

methodology has been employed successfully in Germany and in the US for the evaluation of MEFs for BEV charging loads (Huber et al., 2020; Tamayao et al., 2015). The second option is consumption-based, where the observed system wide demand and corresponding emissions are used to empirically derive MEFs, typically based on the method of Hawkes (2010). This approach enables the integration of renewable sources, electricity imports and exports. Including renewables in the MEF calculation is required once there is a significant share in the mix as there are periods where renewables operate on the margin and so affect calculations of MEFs (Li et al. 2017). Wind power curtailment is a growing issue for the UK electricity system (Joos & Staffell, 2018) and evidence from other markets suggests that solar curtailment is substantially higher for the same share of energy produced (Yasuda et al., 2022). We have therefore chosen to use the consumption-based option with renewables included.

The method given by Hawkes (2010) was used for calculating MEFs based on empirical emissions and demand. The method generates the observed marginal emissions of the system by deriving the relationship between the change in emissions resulting from the change in demand. Two series are produced containing the difference between consecutive half-hourly observations of emissions and demand:

$$\begin{aligned}\Delta E_t &= E_t - E_{t-1}\\ \Delta D_t &= D_t - D_{t-1}\end{aligned} \tag{1}$$

Where, E, is the total emissions of a given pollutant (in grams); D is the total demand of the system (in kWh), for time, t, and the previous half-hourly time step $t-1$. ΔE_t and ΔD_t are calculated for each half-hourly time step. The ordinary least squares regression of these two series yields a linear relationship, where the gradient is the marginal emission factor (in g/kWh). A MEF is calculated for a specific period, where the regression is applied to filtered data from Equation 1. For example, the MEF for the years 2012 and 2019 are given in Fig. 2. In Fig. 3, the MEF is calculated and plotted for each month, and agrees with similar results from previous studies in the UK (Staffell, 2017; Thomson et al., 2017).

Hourly MEFs were derived by aggregating the two series from Equation 1 across each hour of the day; producing a MEF for 1am, 2am and so on. Hourly MEFs were derived for each quarter from 2010 to 2019 yielding a diurnal profile of MEFs. These diurnal MEF profiles are given in Fig. 4 for 2012 and 2019. Hawkes (2010) and Silver-Evans et al. (2012) found that the diurnal profile of MEF is highly sensitive to the daily patterns of generators in the mix and produced similar profiles as those shown in Fig. 4 for 2012 (when the generation mix was more comparable). A prominent example of this is the observation that MEF falls to approximately zero at 1 pm during Q3 2019, as additional demand is met entirely by zero-carbon generators, particularly rooftop solar PV. More precisely, it is met by reducing the amount of these generators which must be curtailed (wasted) due to congestion on the transmission grid at this time of peak coordinated renewable infeed.

3.4. Charging profiles

We used two charging profiles from previous studies, which describe the daily pattern of energy demand required for charging a BEV. The first profile was used to represent the average vehicle in the UK, and we call this the *national* charging profile. The national profile was derived from over 8 million charging events across the UK between 2017 and 18 (Element Energy, 2019). To date, this is the largest aggregation of charging data in the UK, and, as far as we are aware, in the world. This charging profile was published in the National Grid's Future Energy Scenarios (National Grid, 2019). The profile gives the power demand at a one-hour time resolution,

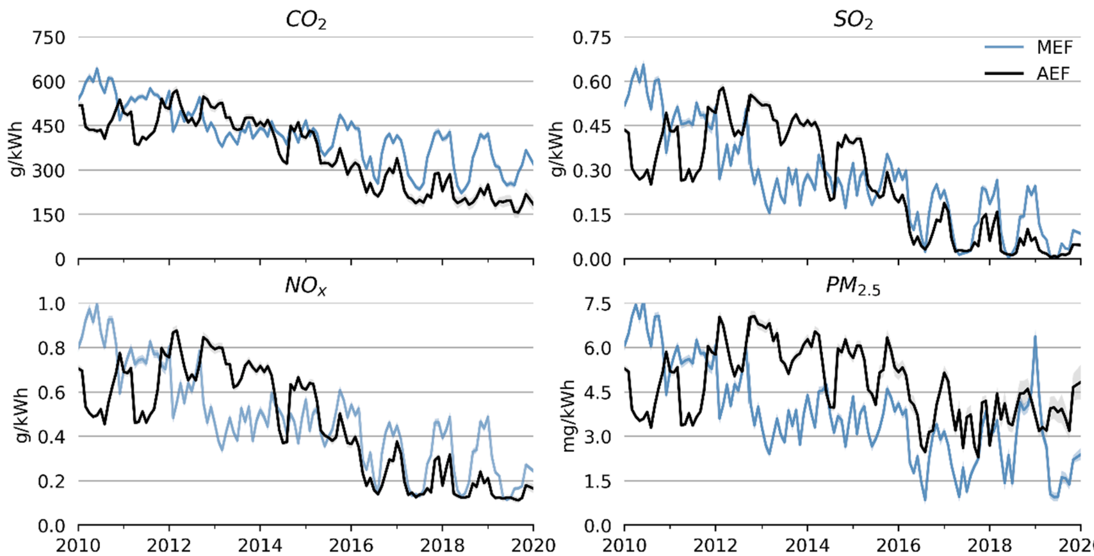

Fig. 3. Marginal and average emissions factors for electricity generation given at monthly resolution. Shaded areas show the 95% confidence interval of the calculated emissions.

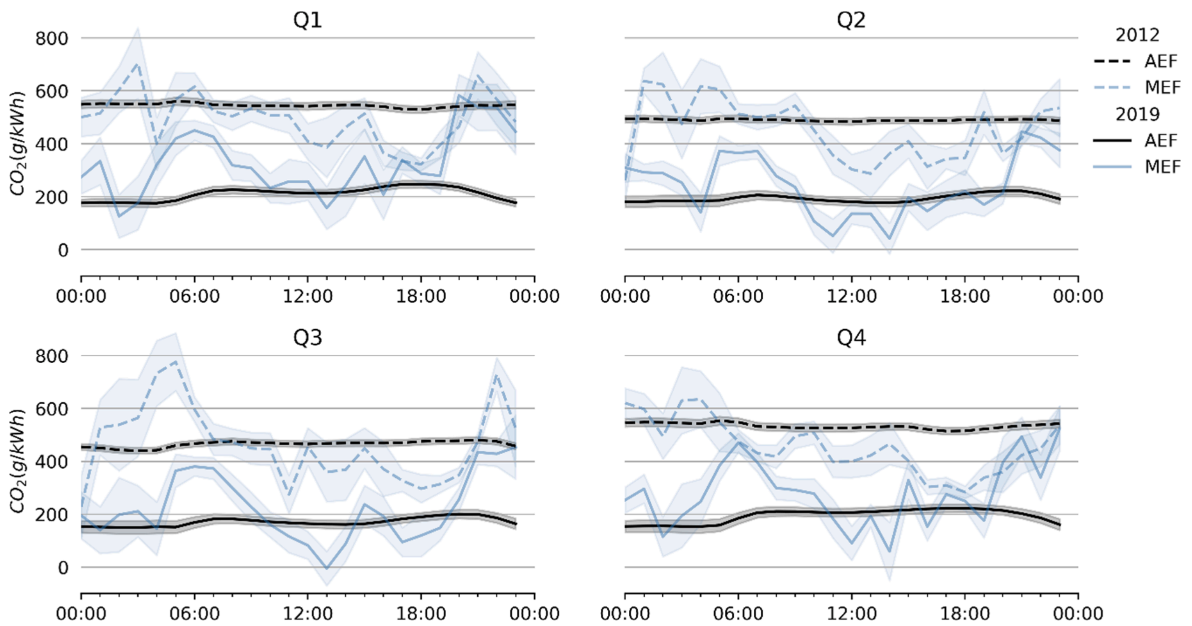

Fig. 4. The 24-hour profile of marginal and average CO_2 emissions for the years 2012 and 2019, by quarter. Area marks 95% confidence intervals.

covering a week in length, the mean profile for a weekday and weekend are given in Fig. 5.

The second charging profile was used to represent the population's mean off-peak or Time-of-Use energy tariff charging strategy, referred to as the *off-peak* charging profile from here on. There is conflicting colloquial terminology for smart charging and off-peak charging, as they both aim to reduce cost, emissions, or both. We distinguish the two by considering off-peak as a fixed charging profile, static on a day-to-day basis. Whereas for smart charging, the charging profile is variable between days and therefore can be responsive to variable renewable electricity generation beyond the day-night cycle for solar photovoltaics. This has latter ramifications for considering whether to use AEFs or MEFs for evaluating these two charging strategies. For *off-peak* charging we used a published charging profile where control of Battery-EV charging was given to the electricity supplier, which delayed charging into the night (Transport Research Laboratory, 2019). The off-peak charging profile is shown in Fig. 5, and was the same for all days of the week.

To compliment to the two real world charging profiles, we simulate two theoretical smart charging profiles. These were created to represent strategies employed in the real world, which are designed to reduce average CO_2 emissions. A wealth of optimisation techniques exists for scheduling BEV smart charging, with most research on either optimising for the distribution system or balancing the transmission system with renewables (Hu et al., 2016). For clarity, we use a simple charge scheduling technique similar to Gan et al. (2013) and apply this to a single model vehicle.

The smart charging profiles were both created retrospectively for each day, choosing the hours with lowest AEF to charge whilst respecting time window constraints. The first chose the 5 lowest carbon hours overnight, from 18:00 to 06:00. The second chose the 5 lowest carbon hours throughout the whole 24-hour period. The first, termed *overnight*, represents the most common method of smart charging currently employed. The second, termed *24-hour*, represents the lowest possible emission scenario, acting as an emission floor for charging for 5 h in a single day, starting at 18:00 and ending at 18:00 the next day. This approach is similar to the methods of Hoehne & Chester (2016), where the charging profile was optimised based on MEFs by Silver-Evans et al. (2012). However, we chose

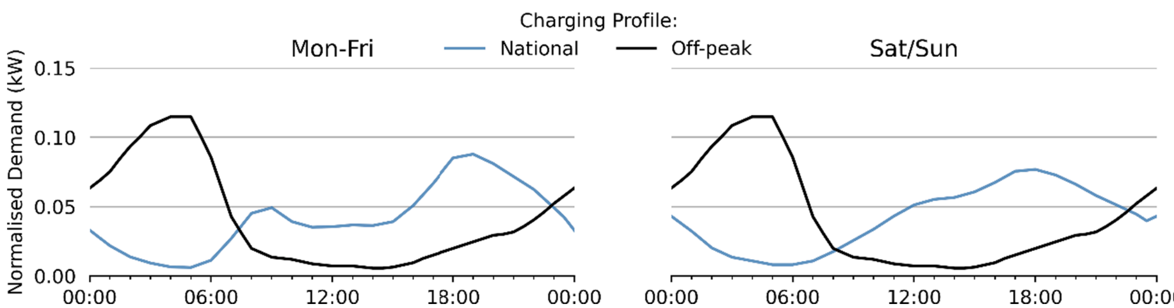

Fig. 5. The two real world charging profiles for electric vehicles used in this study. 'National' gives the mean charging profile for the average BEV in the UK and contains a different charging profile for each day of the week, the mean for the weekday and weekend are given here. 'Off-peak' gives the off-peak charging profile and is the same for each day of the week.

not to optimise charging based on MEFs since current real world smart charging strategies are currently designed to minimise AEFs. For example, two products on sale in the UK currently offer smart charging modes that reduce real time CO_2 emissions (Ohme, 2022; Tweedale, 2022). The 5-hour charge time was chosen to be representative of the time taken to charge 35 kWh with a 7 kW charger. This was intended to represent typical battery capacities of BEVs in the UK from 2010 to 2020, where for example the most popular BEV during this period, the Nissan Leaf (2015–2018), had a capacity of 30 kWh.

As the shape of the charging profile is the key factor in determining emissions per kilometre driven, we normalised each charging profile to draw 1 kWh over a 24-hour period, hence the lower than typical charge speeds shown in Fig. 5 and Fig. 6.

3.5. Losses and efficiencies

For the electricity system we use the UK's measured average transmission and distribution loss of 7.5 %, taken from Staffell (2017). And for the BEV we use the overall electrical supply equipment and vehicle drivetrain efficiency per kilometre from Cox et al. (2018) at 5.26 (4.17 – 7.69, 95 % confidence interval) km/kWh. This single value (with uncertainty) was used to represent the mean BEV efficiency over the 10-year period of this study, whereas in reality BEV efficiencies have likely improved over this period.

3.6. Calculating emissions

The charging profiles were temporally aligned with the electricity generation data. The product of the charging demand, $CD(kWh)$, with the real-time emission intensity of electricity, $EI(g/kWh)$, and with the inverse of transmission and distribution efficiency of the electricity system, η, gives the emissions from charging, $E(g)$, for each time interval, t (30 min). Then summing these products over a time period, T, gives the total emissions during this period, as given in Equation 2. To get the emissions per kilometre, we divide the emissions by the vehicle range gained through charging from the same period. The distance is calculated from the product of the charging demand, CD, and the overall BEV energy consumption per km, $EC(km/kWh)$, for each interval and summing these products over the time period, as given in Equation 3.

$$E_T = \sum_{t \in T} \frac{CD_t \times EI_t}{\eta} \tag{2}$$

$$R_T = \sum_{t \in T} CD_t \times EC \tag{3}$$

This method was applied at the 30-minute time resolution from 2010 up to 2020 for AEF emissions. However, for MEFs, as the emission intensity of electricity was calculated as a 24-hour emission profile for every quarter, the calculations above are applied as above to this quarterly dataset.

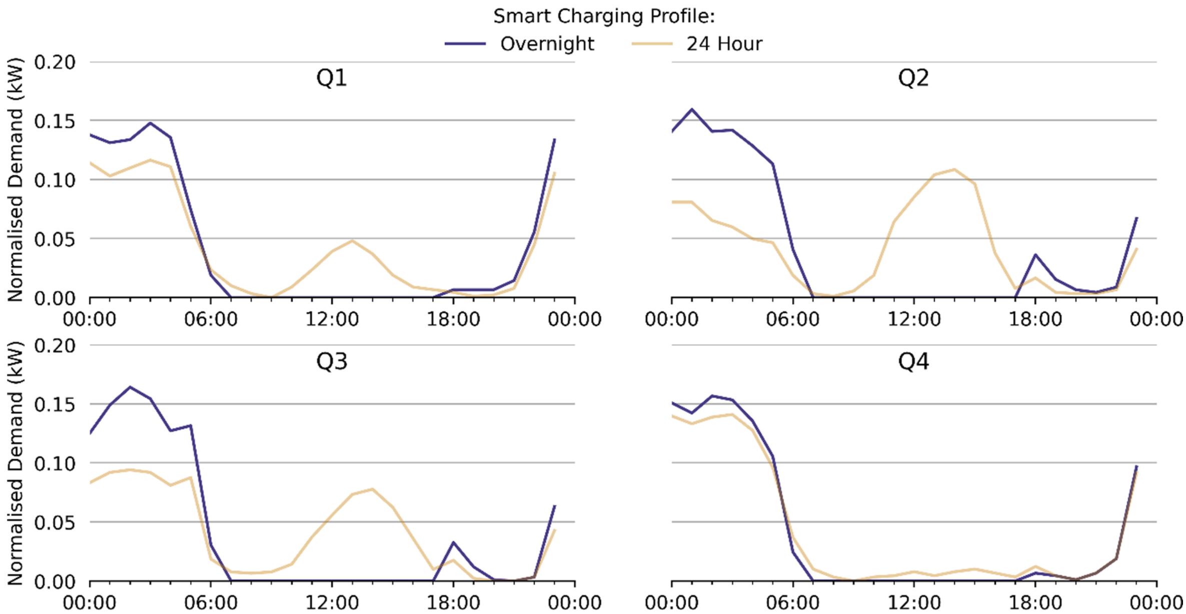

Fig. 6. The two theoretical smart charging profiles for electric vehicles used in this study. Each panel shows the mean charging profile for the two retrospective smart charging strategies for each quarter in 2019. It should be noted that these profiles varied from day to day, unlike the real-world profiles shown in Fig. 5.

3.7. Internal combustion engine vehicle emissions

To frame the emission results in this study, exhaust emissions from new Internal Combustion Engine Vehicles (ICEVs) were compared to the electricity generation emissions for BEVs. This is not intended to be direct comparison on a wheel-to-wheel basis as fuel supply chain emissions are not included for either vehicle technology. Instead, this comparison is used to add context to both the absolute value of the electricity generation emission results and the relative uncertainty presented in this paper.

Exhaust CO_2 emissions for ICEVs were taken from the EEA CO_2 car monitoring database, which contains the type-approval CO_2 emission rate for each new vehicle sold within the EU. This data was obtained for sales of all cars, disaggregated by fuel and technology type, for the UK in 2019. As type approval CO_2 emission rates overestimate the real-world performance of the ICEV (Craglia & Cullen, 2019; Tietge et al., 2017), a correction factor was applied, specified by fuel and technology type. The correction factor from Dornoff et al. (2020) increased CO_2 emissions for diesel cars by 44 %, petrol cars by 37 %, and hybrid cars by 50 %. PHEVs are omitted from this paper due to the added complication surrounding utilisation factors and the large effect this parameter has on fleet average CO_2 emissions (Plötz et al., 2020; Transport & Environment, 2020b). Diesel HEVs were found to be the highest CO_2 emitting ICEV, which illustrates how this technology is being employed to reduce the fuel consumption of high emitting vehicles in the fleet. Air pollutant exhaust emissions were taken from the EMEP/EEA emission inventory guidebook (European Environment Agency, 2019). The advent of real driving emissions testing in the latest Euro 6 standards has produced real-world improvements in NO_x emissions for diesel cars. To reflect this we have reduced NO_x emissions from the EMEP/EEA emission factors in line with the reductions applied in the latest COPERT 5.4 emission factors (Emisia, 2020). These emissions per kilometre for ICEVs are given in Table 1.

4. Results

We first present results for the environmental impacts of charging BEVs in the UK using the *national* charging profile. Next, we show how the time resolution of the method impacts the calculated AEF and MEF emissions. And finally, we compare the different charging strategies to the national charging profile.

4.1. Emissions

Electricity generation emissions resulting from charging BEVs in the UK from 2010 to 2019 are given in Fig. 7 and are summarised for 2019 in Table 2. Emissions have declined since 2012 for all pollutants. The phase out of coal generation was a major reason for this fall in AEF emissions, being displaced by gas, imports and renewables since 2012 (Wilson & Staffell, 2018). $PM_{2.5}$ emissions largely remained constant, due to the increase in biomass generation, which has the highest emission factor for $PM_{2.5}$, balancing out the phase out of coal. The mean AEF and MEF emissions per kilometre in 2019 are given in the bar chart sub-plots of Fig. 7, along with the exhaust emissions of petrol and diesel ICE and hybrids bought in 2019. Electricity generation emissions of CO_2 for BEVs in 2019 were below the exhaust emissions of each of the ICEV vehicle types when considering AEF or MEF emissions. The most comparable emission type between BEVs and the ICEVs was NO_x. This comparison between BEVs and conventional vehicles is followed up in the Discussion section, where we discuss how these charging and exhaust emissions fit into the broader context of lifecycle emissions, where all lifecycle CO_2 sources from each vehicle type are considered.

The evolution of MEF emissions throughout the decade illustrates the change in the mix of marginally operating power plants. At the start of the decade, gas provided most baseload generation and coal was the marginal source, until falling coal prices in 2011–12 reversed these roles, at which point MEF emissions drop below AEF emissions. After this transitional period MEF emissions have not substantially declined, which is due to the remaining reliance on gas to provide marginal generation (Gissey et al., 2018). The steady decline of baseload coal from 2012 caused AEFs to decline back below MEFs in 2015. From 2017, MEF emissions of $PM_{2.5}$ were consistently below AEF emissions due the use of biomass in the UK as baseload generation. As gas was the major marginal generator, with relatively low $PM_{2.5}$ emissions, MEF are lower than AEF $PM_{2.5}$ emissions.

Using the national charging profile emissions per kilometre results in Fig. 7 and Table 2, we answer the first research question in this paper: what emissions were produced in the generation of electricity for supplying BEV charging in the UK from 2010 up to 2020? We answer this using both AEF and MEF emissions. In 2010 using AEF emissions, the generation of electricity supplying BEV charging emitted 95 g CO_2, 112 mg NO_x, 66 mg SO_2, and 0.83 mg $PM_{2.5}$ per kilometre driven for a single vehicle; in the short-run using the MEF

Table 1
Emissions per kilometre for ICEVs. CO_2 emissions are derived from the EEA CO_2 monitoring database using real world corrections for vehicles bought in 2019. Air pollutant emissions of NO_x and $PM_{2.5}$ are taken from the EMEP/EEA emission inventory guidebook. Values in brackets show 95% confidence intervals describing the distribution of emission rates within the vehicle fleet, where for CO_2 this shows the population distribution of type approval WLTP reported values, and for the air pollutants the range shows the distribution of expected real-world emissions from the EMEP/EEA emission inventory guidebook.

Vehicle	CO_2 (g/km)	NO_x (mg/km)	$PM_{2.5}$ (mg/km)
Diesel	194 (119 – 267)	53 (42 – 63)	1.50 (1.24 – 1.76)
Diesel HEV	206 (109 – 303)	11 (9 – 13)	0.30 (0.26 – 0.38)
Petrol	177 (100 – 253)	61 (49 – 73)	1.60 (1.32 – 1.88)
Petrol HEV	144 (95 – 193)	13 (10 – 16)	0.34 (0.28 – 0.40)

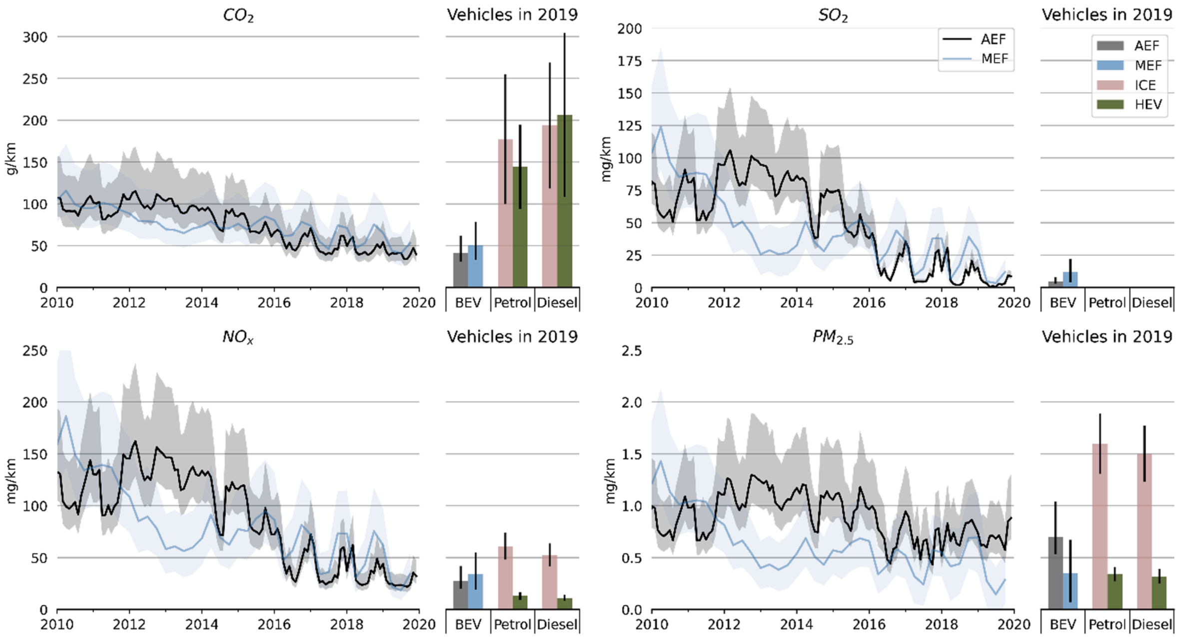

Fig. 7. Marginal and average emission rates per kilometre for the national charging profile. AEFs are given monthly and MEFs given quarterly. To the right of each plot are summary bars for 2019, where both AEF and MEF emissions per kilometre are given for a BEV, in comparison to real world exhaust emissions for new petrol and diesel internal combustion engine (ICE) and hybrid electric vehicles (HEV). Shaded areas in the line plots and error bars in the bar plots for BEVs and ICEVs show the 95% confidence interval. Note that the BEV drivetrain efficiency was assumed to be unchanged throughout this study, and so the changes in emissions evident in this figure are solely due to changes in emissions from power stations.

Table 2
2019 electricity generation emissions per km for the national charging profile, calculated using Average and Marginal emission data from Fig. 7.

Pollutant (unit)	Emission Type	Emissions per km
CO_2	AEF	41.2 (32.0 – 60.5)
(g/km)	MEF	50.7 (34.7 – 77.1)
NO_x	AEF	27.2 (21.1 – 41.0)
(mg/km)	MEF	34.0 (20.0 – 53.8)
SO_2	AEF	4.8 (3.7 – 7.0)
(mg/km)	MEF	12.2 (4.6 – 21.4)
$PM_{2.5}$	AEF	0.696 (0.542 – 1.027)
(mg/km)	MEF	0.349 (0.080 – 0.661)

results, these emissions changed by + 12 %, +46 %, +65 %, and + 52 %, respectively. In 2019, the AEF emissions were 41 g CO_2, 27 mg NO_x, 4.8 mg SO_2, and 0.70 mg $PM_{2.5}$ per kilometre driven; changing by + 23 %, +25 %, +154 %, and −50 % if using MEF emissions, respectively. By the end of 2019 there were 99,000 BEVs on the road in the UK (SMMT, 2019). Using the mean 2019 UK annual mileage of 10,633 km (Department for Transport, 2021), results in 1.05 billion vehicle kilometres driven by BEVs, requiring 0.2 TWh of electricity. This generation of electricity resulted in the emission of 43 kt of CO_2, 28 T of NO_x, 5 T of SO_2, and 0.74 T of $PM_{2.5}$ to supply the fleet of BEVs using the national charging profile using AEF emissions.

4.2. Impact of temporal granularity

To answer the second research question in this paper, on how the time resolution of the method may affect the emissions calculated, we show here the difference in calculated AEF CO_2 emissions when using two different methods. We begin with the method presented throughout this paper (referred to as the temporal method), using a time resolution of 30 min for charging and electricity generation, and assuming the national charging profile. We compare this to the 'non-temporal method', which removes the temporal aspect of charging and electricity generation, taking the mean electricity generation mix over a year as that which supplies the total electricity demand from BEV charging. This is equivalent to assuming constant BEV charging throughout the day, month, and year. This non-temporal method is the most typical in LCA studies due to the simplicity and ease of access to the required data.

We found that there is a growing discrepancy in calculated AEF CO_2 emissions between the two methods. This difference is illustrated in the right-hand panel of Fig. 8 which shows the change in CO_2 emissions of using the non-temporal when compared to the

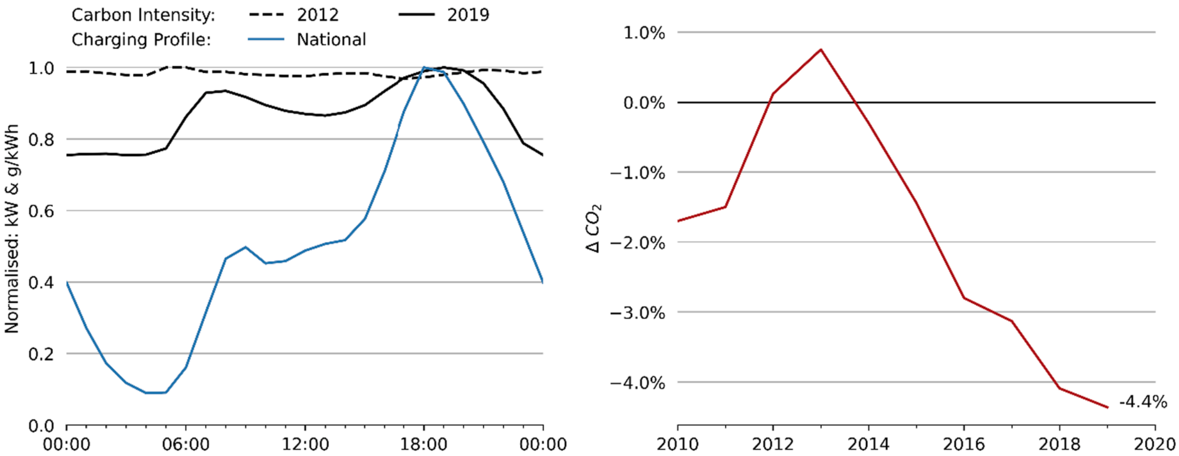

Fig. 8. Left) Carbon intensity of electricity for 2012 and 2019 in dashed and solid black lines, respectively; given with the national charging profile in blue, where all plotted data have been normalised to the maximum value to highlight the phase of the pattern.. Right) The change in calculated CO2 emissions between the temporal and static methods as a percentage of the temporal estimate (negative values show underestimation from the static method). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

temporal method. This shows that by using the non-temporal method CO_2 emissions will be underestimated in 2019 by 4.4.%. This discrepancy is driven by the alignment of the peaks of the national charging profile and the daily pattern of the carbon intensity of electricity, as shown in the left-hand panel of Fig. 8. This shows that the time-resolution of the method chosen will change the CO_2 emissions calculated due the relationship between daily charging and electricity generation patterns.

The third research question regarding marginal emissions is more nuanced due to how MEFs are derived. In the method employed in this paper MEFs were generated across a 24-hour period using data from a quarter of the year (as outlined in section 2.3 Marginal Emissions – MEFs). There are many other time periods a MEF can be generated for, with Fig. 2 showing an example MEF over the entire year for 2012 and 2019. Using the 319 g CO_2/kWh MEF in 2019 from Fig. 2, we find emissions per kilometre of 61 g CO_2 for a BEV. This is 20 % higher than the value presented in Table 2 using the approach outlined in the methods of in this paper. This discrepancy shows that the MEF derivation method will significantly affect the calculated marginal emissions.

4.3. Charging strategies

The results for smart charging are given as the relative change in emissions when compared to the national charging profile. From these results we answer the third research question: How would different BEV charging strategies change these emissions?

The results calculated using MEFs are presented in the left-hand panels of Fig. 9, where the relative change emissions to those of the national charging profile are given on a quarterly timescale. These results are then aggregated in Fig. 10, which shows the mean change in emissions over three time periods: 2010 up to 2015, 2015 up to 2019, and 2019 up to 2020. Short-run CO_2 emissions in 2019 were increased by 11 % for off-peak and 4 % overnight smart charging, whereas 24-hour smart charging decreased them by 9 %. For air pollutants in 2019, both overnight and 24-hour smart charging decreased emissions, whereas off-peak increased emissions. The efficacy of the 24-hour smart charging strategy has grown over time for all emission types. Air pollutant emissions were changed to a greater degree than CO_2 emissions by each of the charging strategies, due to the disproportionate contribution of marginal gas and coal generation to air pollutant emissions over CO_2 emissions.

Results calculated using AEFs are presented on the right-hand panels of Fig. 9 on a monthly timescale. There was a clear seasonal pattern in the relative results for AEFs for each smart charging strategy, where reductions in CO_2 emissions are higher in winter than in summer. This seasonal pattern emerged in 2016 and appears to be increasing in recent years due to the greater daily variation of the carbon intensity of electricity during winter. These trends are summarised in Fig. 10 on the right-hand panels. From Fig. 10, CO_2 emissions were reduced for all charging strategies across all years, with increasing emission reductions from 2010 to 2019. In 2019, CO_2 emissions were reduced by 10 % for off-peak, and 16 % for both overnight and 24-hour smart charging strategies. This pattern of emission reduction for the different charging strategies is seen for NO_x and SO_2. Whereas $PM_{2.5}$ emissions were consistently increased from 2015 onwards since these strategies utilise a greater share of biomass from baseload generation. The different generation mix for each charging strategy is given in Table 3, which helps to explain the results presented in Fig. 9 and Fig. 10. The national charging profile follows a generation mix similar to the UK average mix with additional contribution from gas, coal, and imports. Biomass has the highest $PM_{2.5}$ emissions of any generation type, and as each charging strategy has a greater contribution from biomass than national, $PM_{2.5}$ emissions were increased for each strategy. On average, the overnight and 24-hour smart charging profiles enable a 19 % higher share of charging electricity to come from low-carbon sources relative to the national average profile (68 % versus 49 %).

Fig. 9. The relative impact of the different charging strategies on emission rates, compared those from the national average charging profile. These strategies are the average observed off-peak charging pattern of vehicles, and two hypothetical smart-charging profiles (constrained to overnight hours or available 24-hours a day). Marginal emissions (left) are given on a quarterly timescale and average emissions (right) are given on a monthly timescale.

5. Discussion

In this paper we have calculated the historical electricity generation emissions from charging BEVs using both AEF and MEF emissions. Here we use the definitions of MEF and AEF in literature with the framework set out by Ryan et al. (2016) to propose how BEV charging emissions may have changed from the short-run to the long-run over the past decade.

In the short-run, each new BEV in the UK presents a new load to the electricity system, requiring an increase in output from the marginally operating plants, producing emissions quantified by the MEF results in this paper. Over time each individual vehicle contributes to the overall charging demand of the UK's fleet of BEVs. This fleet-wide pattern of charging demand, which the national charging profile captures, is accommodated into the electricity system through the building of new infrastructure to meet this demand. If the system response to this additional load (i.e., the mix of power stations that is built to serve the additional demand) follows the historical response and remains constant over time then the emissions produced in meeting this fleet wide demand will, in the long-run, follow the real time emission intensity of the electricity, thus corresponding to the AEF emissions given in this paper. However, many financial, environmental and technological aspects of the electricity sector have changed dramatically over the past decades, which will influence the investment decisions of what new capacity to build in the future in different ways to those decisions made in the past. The shape of the charging profile will also affect the mix of technologies chosen to meet this additional demand. The AEF is therefore only one approximation of the emissions produced from charging EVs in long-run, albeit one that is commonly used in the literature (Faria et al., 2013; Foley et al., 2013; Rangaraju et al., 2015; Robinson et al., 2013), possibly due to its ease of calculation.

Methods from Hawkes (2014) may alleviate this issue by using an electricity system model to simulate counterfactual scenarios where BEVs do and do not enter the system, revealing the long-run impact of BEVs on emissions once the system has adjusted the mix of installed capacity. Yet this approach will introduce uncertainties surrounding the electricity system model used to produce the

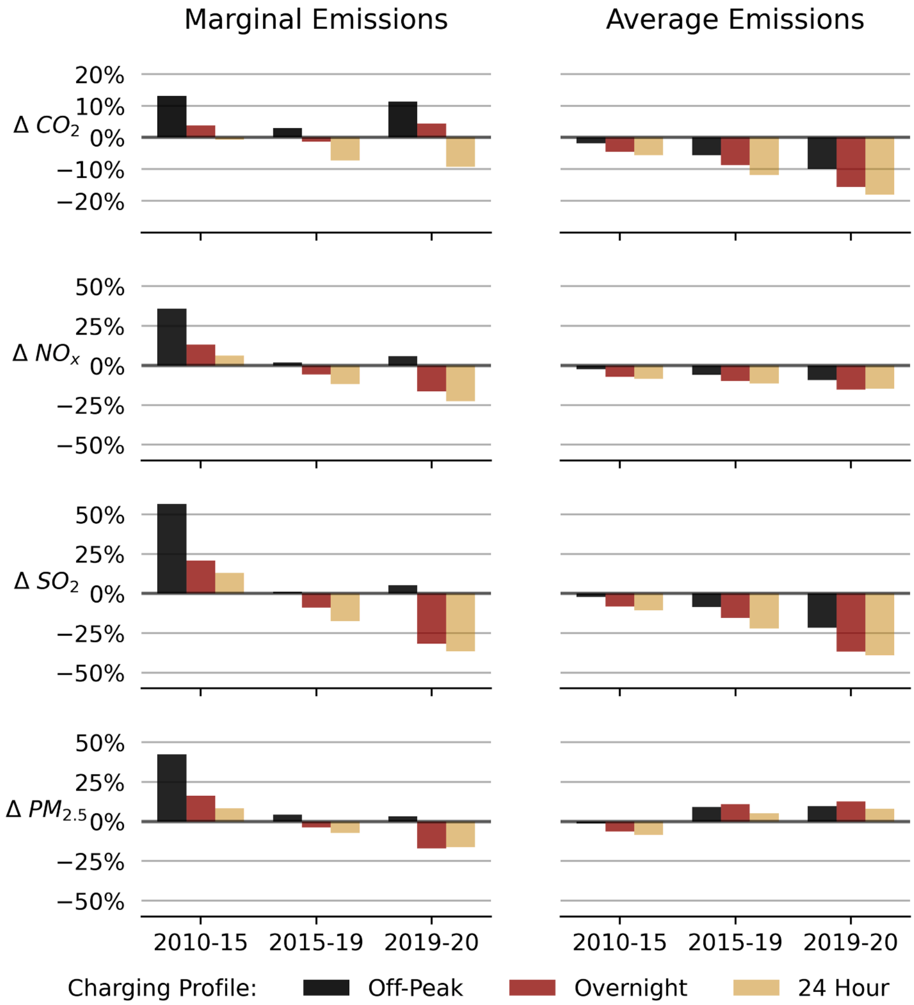

Fig. 10. The mean change in emissions for the different charging strategies from the results in Fig. 9 aggregated across three time periods.

Table 3
Mean generation mix for each charging profile for 2019. * Used to label which charging profile had the highest contribution from the generation type.

	National	Off-Peak	Overnight	24 Hour
Gas	*40.8 %	36.5 %	34.2 %	34.7 %
Nuclear	17.7 %	22.2 %	*24.0 %	21.8 %
Wind	19.8 %	23.6 %	*25.2 %	23.4 %
Imports	*8.2 %	7.1 %	7.0 %	6.8 %
Biomass	6.1 %	7.2 %	*7.5 %	*7.5 %
Solar	4.0 %	1.0 %	0.1 %	*4.3 %
Coal	*2.0 %	1.2 %	0.8 %	1.0 %
Hydro	*1.3 %	1.2 %	1.2 %	1.1 %

counterfactual scenarios, assumptions on the future price of technologies, fuels and emissions. Due to these issues, the emissions produced in the long-run response are not possible to be precisely forecasted with either MEFs or AEFs. Future work could address this issue, which will likely become of greater importance as more BEVs enter the fleet.

Using the MEF and AEF as an approximation for the transition from short to long-run, we found that CO_2 emissions are 23 % higher in the short-run than in the long-run. This difference corresponds to new BEVs incurring an initial increase in emissions (as marginal changes in demand are predominantly met by gas generation) before reducing towards the long-run (where a mix of gas, renewables and nuclear provide most demand) value of 41 g CO_2 per kilometre for the established fleet of BEVs. The time of the transition between short and long-run is not well defined. However, as the national charging profile was taken from the UK's electricity system operator who also publish the current and projected number of BEVs in the UK (National Grid, 2019), this response time may be shorter than changes in load in the past.

To demonstrate how the 23 % increase between AEF and MEF CO_2 emissions may affect overall BEV life cycle emissions, we use the results from a recent LCA to observe how this change affects their conclusions. The LCA found that emissions from electricity generation in the UK were 43 g CO_2 per kilometre, agreeing with our results of 41.2 (32.0–60.5, 95 % confidence intervals) (Transport & Environment, 2020a). The LCA found that the vehicle and battery manufacturing CO_2 emissions were equivalent to 48 g/km, contributing over half of the BEV's total life cycle emissions. If the current marginal impact of EV charging persisted over the entire BEV lifetime, total CO_2 emissions of the BEV would increase by 9.5 g/km or 11 %. For context, this does not alter the conclusions of the LCA since an increase of 142 g/km or 162 g/km would be required to bring the lifetime emissions of the BEV to that of petrol and diesel ICE vehicles, respectively (Transport & Environment, 2020a).

The off-peak charging strategy was fixed on a day-to-day basis fixed as was taken from historical charging data. And so, the off-peak strategy requires using the MEF results for the short-run where the new charging pattern is established. AEF emissions can be used as an approximation of the long-run emissions once a significant amount of BEVs adopt this pattern. Therefore, there was an initial 11 % penalty in CO_2 emissions to switching to off-peak, but in the long-run this strategy may have reduced CO_2 emissions by up to 10 % when compared to the national charging profile in 2019. This reduction in CO_2 emissions was seen to be increasingly seasonal, with the greatest emission reductions occurring in the winter. Using the previous LCA results to frame this emission reduction, the 10 % decrease in CO_2 emissions from off-peak charging would reduce lifetime BEV emissions by 3.3 g/km or 5 %. This strategy does not require every BEV in the fleet to operate with the exact off-peak charging profile described in this paper. Instead, the fleet of vehicles would need to operate on average according to this strategy to produce the long-run emission reductions. This strategy already exists in the real world with many energy suppliers in the UK offering time-of-use tariffs for BEV owners which has been shown to shift charging demand into the evening in other markets (Kim, 2019).

Using the distinction between using AEFs and MEFs from Ryan et al. (2016), where new loads to the electricity system require using MEF emissions or where the load is part of historical demand require AEF emissions, we propose two perspectives on whether to use MEFs or AEFs emissions for the two smart charging strategies used in this study.

The first perspective views the national charging profile as the expected BEV charging load on the system and any short-run divergence from this pattern will constitute using MEFs to quantify the change in emissions. This perspective is the most recognised view in the literature (Ryan et al., 2016). This perspective would warrant using the short-run MEF results for new and existing BEVs employing the two smart charging strategies as these strategies changed charging patterns on daily basis. This perspective finds that CO_2 emissions in 2019 may have increased by 4 % for overnight and decreased by 9 % for 24-hour smart charging strategies. The increase for overnight charging is due to the wrong charging optimisation for this perspective, where the charging algorithm was designed to model smart charging in the real world, which minimise AEFs. From this persecutive and these results, it is likely that the common advice that BEVs should only charge when the sun is shining and the wind is blowing, may only be useful when there is access to 24-hour charging. To improve the efficacy of smart charging in the real world the optimisation should be switched from AEF to MEF emissions, which would require daily MEF forecasts. This method is not yet well established, with only few examples to date. Gai et al. (2019) provides a retrospective analysis where a marginal emissions model was created using the same consumption-based methods used in this study for 2011 and 2017, using total generation output of the system to bin the calculated marginal emission factors. Tu et al. (2020) then use this retrospective model with historical total system output to minimise emissions from charging BEVs. Huber et al. (2020) provides the only prediction-based approach by creating a forecast of marginal emissions for Germany then optimising smart charging to minimise these marginal emissions. The UK has entered a period where electricity supply and demand are balanced but not coordinated, with individual actors either unresponsive to the time-varying carbon intensity of electricity, or employing their own strategies to minimise AEF emissions, as demonstrated through the advent of smart charging. Instead of the current AEF-minimising strategies, there is utility in further work employing methods to minimise MEF emissions during this period. However, in the future, with a high penetration of variable renewables, electricity supply and demand may have to become more tightly coordinated. This dynamic system may render these strategies less relevant as BEV demand will be automatically correlated with renewable output (Boβmann & Staffell, 2015; Lund & Kempton, 2008).

For the second perspective, we propose that the two smart charging scenarios were historical loads on the system, despite the two profiles being retrospectively created. This perspective represents BEVs in the real world that were already utilising smart charging technologies between 2010 and 2020. And so, as this load was historical and part of the existing overall demand on the system, the emissions produced would require using AEFs. In this case both the overnight and 24-hour smart charging strategies may have reduced CO_2 emissions by over 16 % in 2019.

We determined that by removing the time resolution of the method changed the calculated AEF emissions from the generation of electricity for BEVs by up to 4.4 % for the UK in 2019. This result is within the range observed by Miller et al. (2020) in the US, but below the observed maximum of 11 % found for California. This discrepancy is due to the different patterns of BEV charging demand and emission intensity of electricity, where for example the largest discrepancy in the US was in California which has the 'Duck Curve' of emission intensity due to extensive solar PV deployment. In the context of BEV LCAs for the UK, this change is small when compared to the other variability reported in the literature for electricity generation emissions (Marmiroli et al., 2018). Other countries will experience unique emission discrepancies with methodologies using different time resolutions as they will have distinct patterns of daily charging and daily electricity emission intensity. For the marginal approach, the observed discrepancy shows that emissions calculated will be highly sensitive to choices regarding the temporal aspects of the method. And so, future comparisons of marginal emissions between studies should aim to use the same methods and time period choices for deriving MEFs.

The results given in this study present emissions of air pollutants from different sources side by side, for example ICE exhaust emissions were given alongside power station emissions in Fig. 7. This direct comparison is not intended to indicate the upstream health impacts as the location of the sources are critical for estimating population exposure. As road transport is highly correlated with populated areas the emissions from vehicles have a much higher impact on local scale air quality impacts than power stations emissions and this is reflected in air pollutant damage costs in the UK (Department for Environment Food & Rural Affairs, 2021). However, both sources will have long-range impacts. To determine these upstream impacts the emissions presented in this study could be paired with an air quality simulation tool using a methodology such as that from Soret et al. (2014).

6. Conclusions

In this study we paired national scale charging data with the corresponding electricity generation data. This enabled the first nationally representative calculation of average and marginal emissions resulting from BEV charging using the highly time resolved methods in this paper.

We found that electricity generation emissions produced due to the charging demand from the fleet of BEVs in the UK steadily reduced from 2012 to 2019. A typically charged BEV in 2019 in the UK was responsible for 41 g CO_2, 27 mg NO_x, and 0.7 mg $PM_{2.5}$ per kilometre driven. For a new BEV entering the fleet in 2019, where the new charging demand is considered marginal in the short-run, these emissions change by + 23 %, +25 %, −50 % for CO_2, NO_x, and $PM_{2.5,}$ respectively. The air pollutant emissions found here should be considered with the other emissions associated with BEVs, such as $PM_{2.5}$ non-exhaust emissions on the road, to appreciate how BEVs are not zero-emission vehicles.

Methods which do not use charging profiles or time varying electricity generation data will underestimate CO_2 emissions by 4.4 % in 2019. As this method is most typically used in LCAs, where the 4 % increase in electricity generation emissions is unlikely to change conclusions of an LCA and may be used as an approximation of the true emissions from electricity generation. This discrepancy will be distinct for each country and change over time due to the unique daily pattern of electricity generation and BEV charging. Methods which calculate marginal emissions from BEV charging will be highly sensitive to the chosen derivation period and whether the method also employ daily charging profiles.

Consistent off-peak charging may reduce CO_2 emissions by 10 % for BEVs in the UK due to the greater utilisation of baseload generation. As real-world smart charging technologies are designed to minimise average emissions, they may unintentionally produce more emissions due how marginal demand is currently met in the UK. Marginal emissions do not follow the same daily patterns as average emissions and so future smart charging technologies should shift from minimising average emissions to minimising marginal emissions. Further work is needed to inform BEV users on how to charge their vehicle to minimise marginal emissions in the short-run.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2022.103430.

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