

Emissions of electric vehicle charging in future scenarios

The effects of time of charging

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Abstract

Electrification of transport is an important option to reduce greenhouse gas emissions. Although many studies have analyzed emission implications of electric vehicle charging, time-specific emission effects of charging are inadequately understood. Here, we combine climate protection scenarios for Europe for the year 2050, detailed power system simulation at hourly time steps, and life cycle assessment of electricity in order to explore the influence of time on the greenhouse gas emissions associated with electric vehicle charging for representative days. We consider both average and short-term marginal emissions. We find that the mix of electricity generation technologies, and thus, also the emissions of charging, vary appreciably across the 24-h day. In our estimates for Europe for 2050, an assumed day-charging regime yields one-third-to-one-half lower average emissions than an assumed night-charging regime. This is owing to high fractions of solar PV in the electricity mix during daytime and more reliance on natural gas electricity in the late evening and night. The effect is stronger during summer months than during winter months, with day charging causing one-half-to-two-thirds lower emissions than night charging during summer. Also, when short-term marginal electricity is assumed, emissions tend to be lower with day charging because of contributions from nuclear electricity during the day. However, the results for short-term marginal electricity have high uncertainty. Overall, our results suggest a need for electric vehicle charging policies and emission assessments to take into consideration variations in electricity mixes and time profiles of vehicle charging over the 24-h day.

KEYWORDS

electricity scenarios, greenhouse gas emissions, industrial ecology, integrated assessment model, life cycle assessment, power system model

1 | INTRODUCTION

Switching from petroleum-burning transport to transport powered by climate-friendly electricity is an important strategy according to climate stabilization scenarios (Figure 1; Luderer et al., 2016; Tran et al., 2012; Williams et al., 2012). Understanding the current and future emissions associated with electric vehicle charging is a key component to formulating effective electrification strategies (Cox et al., 2018; Ellingsen & Hung, 2018;

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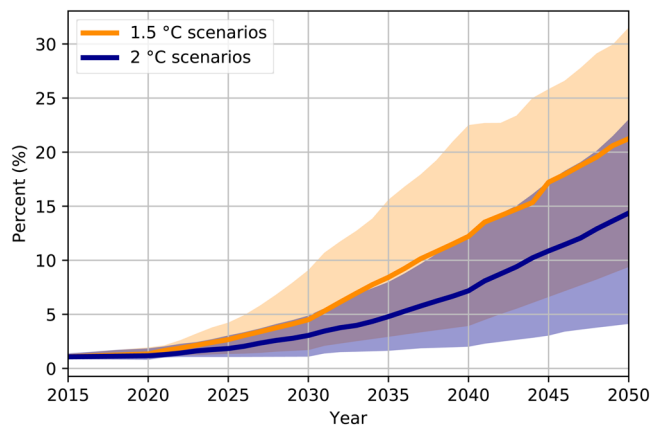


FIGURE 1 Global share of electricity in transport final energy (median and 10–90% range) in 1.5°C and 2°C climate protection scenarios from the IPCC special report on global warming of 1.5°C (IPCC, 2018). The figure is based on data downloaded from the IAM 1.5°C Scenario Explorer and Data (Huppmann et al., 2018). Median values and 10–90% ranges are based on a total number of 77 1.5°C scenarios and 121 2°C scenarios. Underlying data used to create this figure can be found in Supporting Information S2

Knobloch et al., 2020). At the same time, developing such an understanding is a challenge, owing to the location- and time-specific character of both electricity generation and vehicle charging (Messagie et al., 2014; Vuarnoz & Jusselme, 2018); to uncertainty surrounding future electricity generation mixes (relying with different degrees on, e.g., wind, solar and natural gas energy) (Krey et al., 2013); and generally to the high level of sophistication of modern power systems, with numerous interacting generation, transformation, transmission, distribution, and end-use technologies as well as consumer behavior (Amjad et al., 2018; Arvesen et al., 2015; Lund et al., 2015; McCollum et al., 2017).

A wide variety of methods are in use to attribute emissions to specific electrical loads (Ryan et al., 2016). Previous electric vehicle studies have explored aspects of vehicle charging from various perspectives and using different kinds of data. Many studies deal with current power systems, while some studies use scenarios to look into the future (Calnan et al., 2013; Jochem et al., 2015). Some studies explore hypothetical charging regimes (e.g., Coignard et al., 2018; Tamayao et al., 2015), others derive charging patterns from detailed tests for a small number of vehicles (Rangaraju et al., 2015), from travel surveys covering a larger number of vehicles (Crossin & Doherty, 2016; Jochem et al., 2015) or from data from websites and fleet tests (Plötz et al., 2017). A number of studies examine charging time in the context of electricity supply and demand balancing, but do not quantify emissions (e.g., Babrowski et al., 2014; Coignard et al., 2018; Khoo et al., 2014; Sadeghianpourhamami et al., 2018; Wulff et al., 2020). Other analyses quantify only direct emissions of electricity generation (i.e., emissions occurring in the energy conversion process itself) (Donateo et al., 2015; Ensslen et al., 2017; Jochem et al., 2015), while yet others also consider indirect emissions of electricity (such as emissions occurring in transport of fuels to power plant or manufacturing of power plant infrastructure) (Garcia et al., 2018). With few exceptions (Tamayao et al., 2015; Xu et al., 2020), studies focus on limited geographical regions and do not explicitly consider electricity trade across regional boundaries. To our knowledge, few studies undertaken at a large geographical scale and with high temporal resolution have examined both direct and indirect emissions of electric vehicle electricity in future scenarios with a changed mix of energy sources.

Several existing studies have found that time-shifting vehicle charging to outside of morning or evening peak loads is beneficial from an emissions point of view (Axsen et al., 2011; Baumann et al., 2019; Coignard et al., 2018; Foley et al., 2013; Nunes et al., 2015; Rangaraju et al., 2015; Xu et al., 2020). The effects of varying charging time typically increase with higher shares of renewable electricity supply (Crossin & Doherty, 2016; Ensslen et al., 2017; Faria et al., 2013); thus they are likely to increase also in the future as power systems become increasingly reliant on renewable energy. Given current power systems, direct emissions from power stations typically dominate emissions associated with electric vehicle charging (Ryan et al., 2016), but this may no longer be the case in future power systems that are dominated by renewable supply (Pehl et al., 2017).

We explore the greenhouse gas emissions of electric vehicle charging in Europe in year 2050 in two climate protection scenarios. In particular, we study the effects of vehicle charging time (time of day) on emissions. To do so, we combine climate stabilization scenarios that define aggregated characteristics of power systems in the context of economy-wide climate change mitigation policies, detailed power system modeling that determines energy balances (electricity generation, consumption, trade, losses in transmission) at an hourly time resolution and with consideration of inter-annual variability of weather, and future-oriented life cycle analysis that quantifies direct and indirect emissions of electricity with consideration of future technological progress. We quantify emissions for three stylized charging profiles (flat, day, and night charging). The goal of investigating stylized charging choices, as opposed to estimates based on observations, is to gain insights regarding the effects of charging time on charging emissions under scenarios of future electricity mixes, but without considerations of additional complexities such as changing business models (e.g., private versus shared mobility, vehicle-to-grid [V2G] services) and vehicle characteristics (e.g., battery size, autonomous vehicles) in the future. From a methodological perspective, our study adds to a growing body of literature combining life cycle assessment and energy system or scenario modeling approaches (e.g., Arvesen et al., 2018; Blanco et al., 2019; Boubault et al., 2019; Astudillo et al., 2019; McDowall et al., 2018; Mendoza Beltran et al., 2020; Sebastian & Maik, 2017; Volkart et al., 2018; Xu et al., 2020; Tokimatsu et al., 2020).

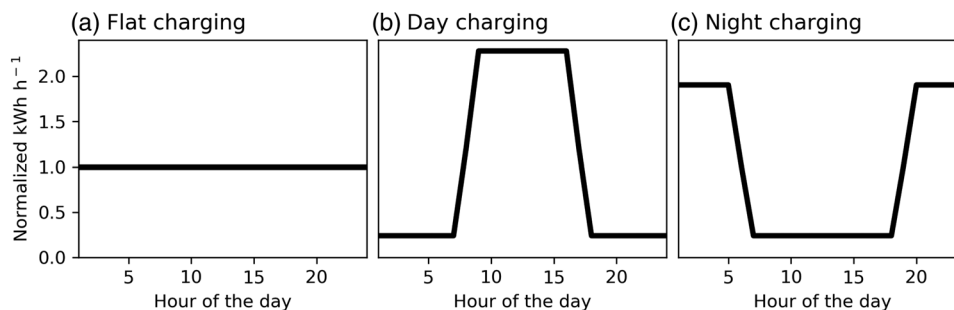


FIGURE 2 Hourly electric vehicle charging load for three charging profiles: flat charging (a), day charging (b), and night charging (c). Vertical axes are normalized to the average electric vehicle power demand across the 24-hour day. Underlying data used to create this figure can be found in Supporting Information S2

2 | METHODS

2.1 | Scenario framework

Scenarios from the process-detailed integrated assessment model MESSAGE form a framework for our assessment by providing numbers for key governing parameters, as will be explained below. MESSAGE is a well-established model for exploring strategies for mitigating climate change (Krey et al., 2016). Scenarios from MESSAGE are used, for example, in reports by the IPCC (IPCC, 2018) and the Global Energy Assessment (GEA, 2012). While MESSAGE represents electricity systems with low levels of geographical and temporal detail, it provides insights into possible long-term evolutions and aggregated characteristics. Unlike sectoral models (such as dedicated power sector models), MESSAGE covers all sectors of the economy with a consistent and coherent approach. Thus, we can obtain from MESSAGE values pertaining to the electricity and transport sectors (including fuel and carbon prices) that are consistent with the full economy in a climate change mitigation context.

Here, we explore MESSAGE results for the year 2050 for two climate protection scenarios (showing >50% chance of staying below 2°C global warming) (Riahi et al., 2015), relying with different degrees on wind, solar, nuclear, and natural gas energy. The FullTech-450-OPT scenario (henceforth “FullTech”) is a default scenario assuming full technology availability, and, notably, includes significant deployment of natural gas power combined with carbon capture and storage (CCS). The second scenario, NoCCS-450-OPT (henceforth “NoCCS”), excludes the use of CCS in the power sector. Consequently, it has increased use of electricity from solar and nuclear energy. There is no use of electricity from coal in either scenario. MESSAGE distinguishes two aggregate European regions (Western Europe and Eastern Europe) (Krey et al., 2016).

For the current analysis, the parameter values provided by MESSAGE are: (i) installed capacities for nuclear and thermal-based electricity; (ii) annual electricity generation for electricity from wind, hydro and solar energy; (iii) natural gas, oil, and biomass fuel prices; (iv) carbon prices; and (v) the overall and transport sector demands for electricity for the studied areas.

2.2 | Time profiles for electric vehicle charging

We investigate three stylized time profiles for electric vehicle charging: flat charging, day charging, and night charging (Figure 2). Flat charging assumes constant charging loads across the 24-h day; day charging assumes that electricity loads are concentrated during daytime (as may be the case if vehicles are predominantly charged at workplaces); while night charging assumes loads are concentrated during night (consistent with privately owned vehicles being predominantly charged at home). Given the hypothetical character of our investigation and in order to simplify the analysis, we treat the charging profiles as generic across countries and across weekdays (i.e., we do not distinguish between working days and weekends). Another simplification is that we analyze total energy requirements for charging without explicitly representing battery only electric vehicles and plug-in hybrid electric vehicles.

2.3 | Power system modeling

Within the scenario framework provided by the MESSAGE model (see Section 2.1), we employ the detailed power system optimization model EMPS (Wolfgang et al., 2009; SINTEF, no year) to determine the hourly operation and balancing of European power systems across the whole year. EMPS is widely used in Nordic countries (Norway in particular) by power producers, transmission system operators, regulators, research institutions, and other institutions. EMPS minimizes the expected cost (or maximize the socio-economic benefit) in the full system, considering all constraints and

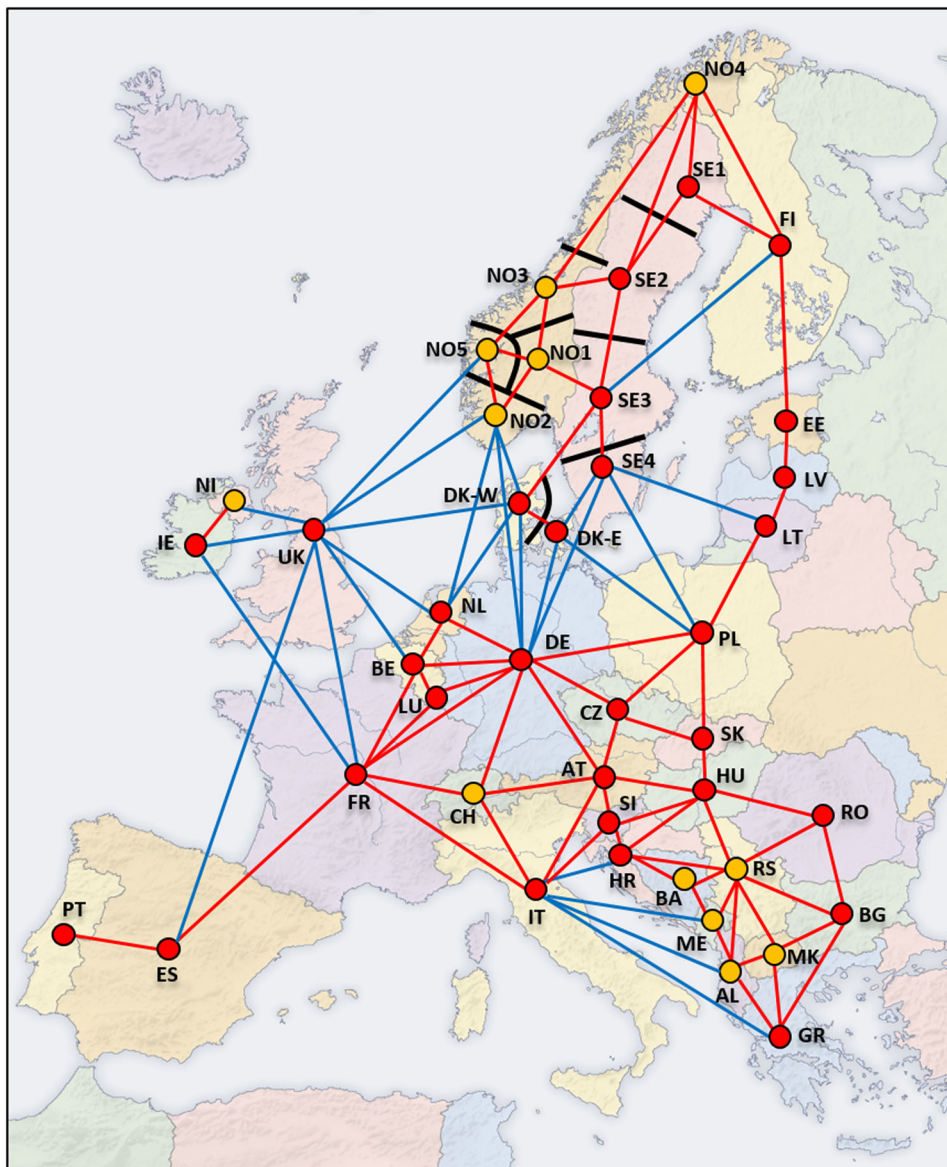


FIGURE 3 Schematic representation of the European power system modeled in EMPS for the current study. Core inputs for the model setup are data from Capros et al. (2016) for the EU-28 countries (red areas) and ENTSO-E (2016) (orange areas). Red lines depict onshore, blue lines offshore connections

under assumptions of well-functioning (ideal) electricity markets. While EMPS is particularly detailed in its treatment of hydropower in Norway and Sweden (calculating the marginal cost of hydropower for each area using stochastic dynamic programming), the model is also capable of simulating the power system across Europe (Figure 3) using a heuristic approach. The outcome of the runs for the different EMPS scenarios (based on the MESSAGE data) carried out for the current work, are inventories of hourly generation and demand, generation mix, trade and prices of electricity for individual area nodes. Inter-year variability due to weather affects the long-term planning of electricity networks (Wolfgang et al., 2009; Zeyringer et al., 2018). EMPS captures inter-year variability through representation of 75 historical climate-years differentiated by climatic distinctions (precipitation, wind speed, solar irradiation) for geographical areas in a linear problem formulation. In the present study, we use an average of all 75 climate-years.

As was explained in Section 2.1, scenario-specific results from MESSAGE for two aggregate European regions are incorporated into the EMPS modeling. Guided by existing scenario literature that have a country-level resolution (Capros et al., 2016; Kasten et al., 2016), we make assumptions in order to disaggregate data from the two aggregate Europe regions in MESSAGE into transmission grid nodes defined in EMPS (Figure 3). Also, we make assumptions in order to assign electricity generation technologies defined in MESSAGE to corresponding technologies defined in EMPS (Table S1-1, Supporting Information S1).

Future extensions to power transmission grids are considered in EMPS based on grid development plans from the European Network of Transmission System Operators for Electricity for year 2040 (ENTSO-E, 2018), since no development plans beyond 2040 were available at the time of analysis. Energy transfers between the nodes depend on transmission capacities between the nodes, based on nodal demand, production capacity and marginal production costs. Nodal energy prices are established on the basis of the surrounding generation mix, energy trades, and congestions. A detailed power flow analysis is beyond the scope of this study.

2.4 | Production or consumption perspective

We study country-level electricity generation in both production-based and in consumption-based terms (Moro & Lonza, 2017; Qu et al., 2018). The production-based perspective means that a country is assigned the domestically produced electricity to satisfy demand in that country, independent of any net imports of electricity from other countries using different technologies for electricity production. The consumption-based perspective, on the other hand, accounts for trade of electricity between countries. We quantify consumption-based electricity of a country as the electricity production and/or net import of that country to satisfy demand in that country, taking into consideration the specific electricity mixes of net imported electricity¹. Trade of electricity between country nodes is a model outcome of EMPS.

While there are many approaches to calculate consumption electricity mixes, we use the flow tracing method, which is also used in Tranberg et al. (2019). In this method, it is assumed that each node is a perfectly homogeneous market, and that imported electricity thus has the same composition as the consumption mix of the exporting country. Conceptually and mathematically, this calculation is analogous to the Leontief approach used in lifecycle assessment (LCA) and input-output analysis.

Note that while country-level results vary depending on the choice of production or consumption accounting, aggregated Europe electricity mixes are independent of this choice in our analysis.

2.5 | Average or marginal perspective

As in some prior literature (Gai et al., 2019; Jochem et al., 2015; Richardson, 2013), we consider both average and short-term marginal electricity generation. The former assumption implies that all concurrent electricity loads—irrespective of whether it is an “existing” or “additional” load—are assigned the same mix of electricity generation sources. In contrast, the latter assumption takes into consideration short-term marginal electricity generation technologies for a load classified as “additional”, for example, a load from electric vehicle charging. Consistent with the logic of attributed (assigned) responsibility of total burdens (Majeau-Bettez et al., 2018), our estimations of average electricity mixes are based on total electricity system supply and demand for each hour, and are not specifically affected by the magnitude of electricity demand from electric vehicles. Conversely, following a consequential logic (Majeau-Bettez et al., 2018), our estimations of marginal electricity mixes take into consideration the additional electricity demand from electric vehicles specifically. It is important to note that short-term marginal emissions aim to capture how emissions change in the short run when a demand is changed. They are not measures of the long-term marginal effect of adding electric vehicles to the system, as this would require calculation of marginal added investments (Amor et al., 2014; Vandepaer et al., 2018; Wangenstein, 2011).

In order to compute the short-term marginal mixes, we run EMPS for a full year two times, once with and once without specific consideration of country-specific electric vehicle electricity demand (Section 2.6). The short-term marginal electricity generation mix is then derived from the difference in electricity production for each electricity production technology between the two model runs.

2.6 | Electricity demand for electric vehicle charging

Estimates of electricity demand for vehicle charging are used for the computation of marginal electricity mixes, as explained in Section 2.5. The estimations are calculated as follows. As a starting point, we take MESSAGE results for overall electricity use in the transport sector for the two Europe regions defined in MESSAGE. We multiply these results by 70%, assuming electric vehicles represent 70% of overall electricity use in the transport sector. Then, we disaggregate the electric vehicle electricity demands to individual country-level, guided by the total electricity demand of each country (available from EMPS modeling) and by differences in the degrees of vehicle electrification between countries in a scenario for year 2050 (“EV-mid scenario” of Kasten et al., 2016). Table S1-2, Supporting Information S1, provides the estimated electricity demands by country for FullTech and NoCCS.

¹ An export from a country does not influence the consumption mix of the exporting country, only of the importing country.

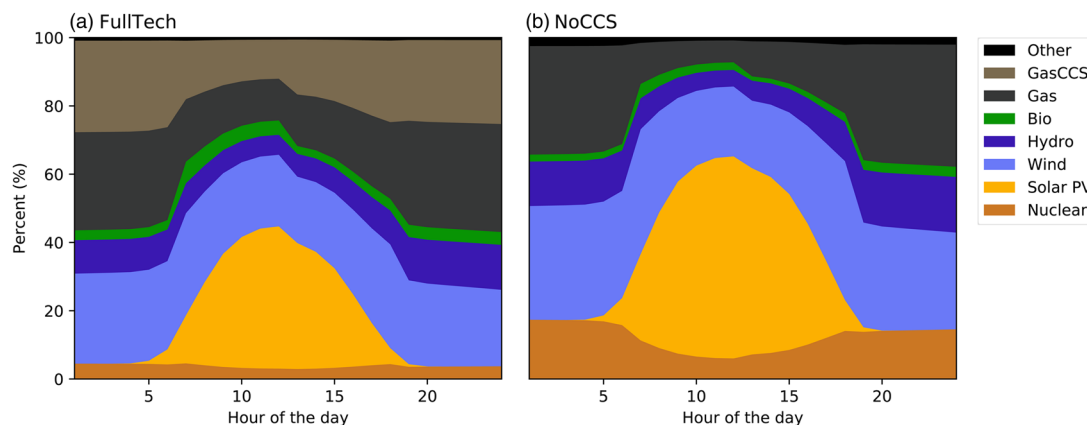


FIGURE 4 Hourly composition of average electricity generation for FullTech (a) and NoCCS (b) scenarios in year 2050. The results represent a European average for an average 24-h day of the year 2050. "Other" refers to other renewable energy sources. Underlying data used to create this figure can be found in Supporting Information S2

2.7 | Life cycle analysis coefficients

We derive coefficients for the life cycle (or "well-to-wheel") greenhouse gas emissions of electricity generation from the THEMIS scenario-LCA model. THEMIS feeds future scenarios of technological progress into the model; this makes the model more representative of future scenarios than LCA models with fixed technology descriptions (Gibon et al., 2015)². THEMIS was first applied in a report published by the UNEP International Resource Panel (Hertwich et al., 2016) and related studies (Gibon et al., 2015; Hertwich et al., 2015), and later by a number of future-oriented LCA studies (e.g., Bergesen et al., 2017; Berrill & Hertwich, 2018; Gibon et al., 2017; Gunnar Luderer et al., 2019; Pehl et al., 2017; Wu et al., 2019).

We implement life cycle inventory data for electricity generation used in Arvesen et al. (2018), Gibon et al. (2017), and Pehl et al. (2017) into THEMIS, and derive LCA coefficients assumed to be representative for Europe for the year 2050 in a 2°C scenario. The life cycle inventory data cover full technology life cycles (including the production, operation and decommissioning life cycle stages of power plants), and supply chains (resource extraction, materials processing, manufacturing, transport, etc.)³. For biopower, we assume a 50–50 split of biomass from forest residues and purpose-grown energy crops (Arvesen et al., 2018), and include CO₂ emissions related to direct and indirect land use changes of purpose-grown energy crops (Pehl et al., 2017). Notably, significant future technological progress is covered for solar photovoltaics (PV) electricity, through projected improvements in energy and material efficiencies, and a projected shift away from crystalline silicon PV and towards thin-film PV (Bergesen et al., 2014).

The coefficients for life cycle greenhouse gas emissions of electricity generated in year 2050 are as follows: 7.6 g CO₂e kWh⁻¹ for nuclear, 12 g CO₂e kWh⁻¹ for solar PV, 7.6 g CO₂e kWh⁻¹ for wind, 35 g CO₂e kWh⁻¹ for hydro, 120 g CO₂e kWh⁻¹ for biomass, 440 g CO₂e kWh⁻¹ for natural gas, and 190 g CO₂e kWh⁻¹ for natural gas with CCS. We map the technology classifications of EMPS and THEMIS based on the best available matches. We assume the same emission coefficient for oil as for gas electricity and subsume oil under the "gas" category in Figures 4–8 (oil electricity contributes negligibly (<0.1%) of total electricity in both scenarios investigated for Europe). Similarly, we assume the same emission coefficient for coal with CCS as for natural gas with CCS (coal with CCS contributes <0.3% of total electricity). For an overview and more details on the technology mapping, see Table S1-1, Supporting Information S1.

We include emissions caused by country-specific losses in electricity transmission and distribution, based on statistics for the year 2014 (IEA, 2018). Overall for Europe, transmission and distribution losses amount to 6–7% of total electricity generated in our analysis.

² Scenarios for future changes in electricity mixes and selected industrial processes (aluminum, copper, nickel, iron and steel, metallurgical grade silicon, flat glass, zinc, and clinker production) are incorporated into the model, as explained in Gibon et al. (2015). Besides electricity mixes, technology changes are particularly significant for PV (based on Bergesen et al. 2014) and bioelectricity (Pehl et al. 2017; Arvesen et al. 2018).

³ For the sake of simplicity, we aggregate emissions associated with the three power plant life cycle stages (production, operation, decommissioning) into one LCA coefficient, and use the same coefficient for average and marginal analyses. We recognize that in doing so, we disregard that emissions associated with the different stages occur in different years (a point previously made by others, e.g., Arvesen and Hertwich, 2011; Usubiaga et al., 2017; Hamilton et al., 2017). We also recognize that one could argue that because our estimations of marginal electricity mixes do not consider marginal added power plant investments (Section 2.5) the LCA coefficients used for marginal analysis should exclude power plant infrastructure emissions. However, such conceptual discussion or clarification on marginal computations are beyond the scope of the current work. In practice, the marginal emissions results of the current study are dominated by contributions from natural gas-based power (as will be shown later in Figure 8, which again are dominated by operational stage emissions, with only insignificant contributions from infrastructure elements).

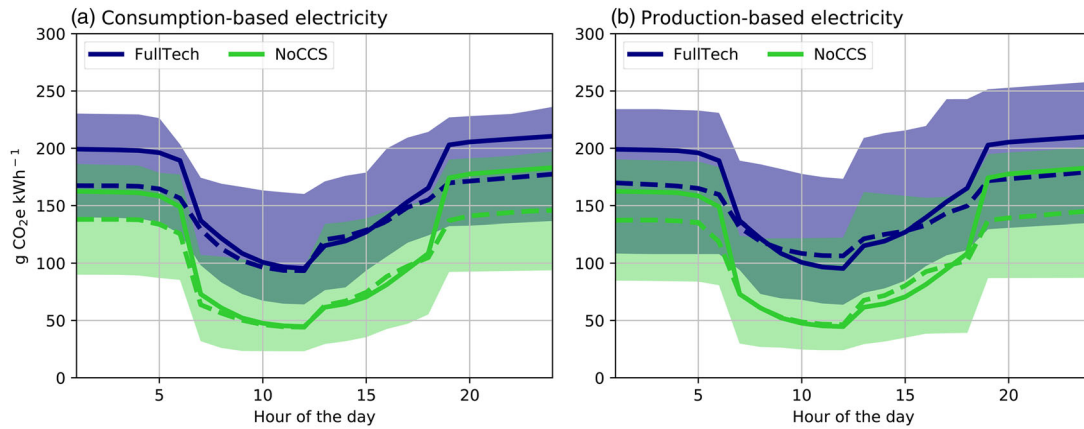
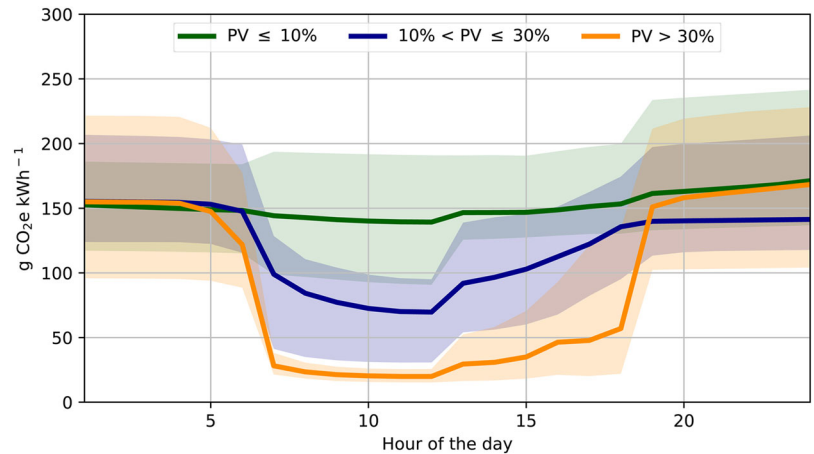


FIGURE 5 Hourly greenhouse gas emission intensity of average electricity generation for an average 24-h day of the year for consumption-based electricity (a) and production-based electricity (b), and for FullTech and NoCCS scenarios. Solid lines represent Europe average; dotted lines represent a median across individual countries in Europe; shaded areas represent 25–75% range across individual countries. The Europe-wide averages (i.e., the solid lines) are the same in (a) and (b), as these averages are unaffected by the choice of consumption- or production-based electricity. Underlying data used to create this figure can be found in Supporting Information S2

FIGURE 6 Hourly greenhouse gas emission intensity of average electricity generation for an average 24-h day of year 2050 for countries with low ($\leq 10\%$), medium ($> 10\%$ and $\leq 30\%$) and high shares ($> 30\%$) of solar PV in electricity generation, using consumption-based accounting. Solid lines represent Europe average; shaded areas represent 25–75% range across individual countries. Results for FullTech and NoCCS are combined in this figure (i.e., each country has two sets of results, one for FullTech and one for NoCCS). Underlying data used to create this figure can be found in Supporting Information S2



3 | RESULTS

3.1 | Electricity generation

The results of our hourly electricity system modeling for Europe for year 2050 show that with future high penetration of solar photovoltaic (PV) electricity, there are considerable variations in the mix of electricity generation technologies across the 24-h day (Figure 4). During the year, solar PV generates an average of 42% and 59% of total electricity at midday in FullTech and NoCCS scenarios, respectively. In addition, wind power tends to have its maximum generation in late afternoon or early evening, but this pattern is much less clear (the variability is less regular) and thus less important than that of solar PV.

The relatively high shares of solar PV during daytime coincide with relatively low shares of natural gas electricity (with or without CCS) and, to a lesser extent, hydropower (Figure 4a,b). In NoCCS, there is in addition a drop in nuclear power during daytime (Figure 4b). These results reflect the operational flexibilities of natural gas and nuclear power plants and hydropower reservoirs. Bioelectricity also contributes with system flexibility, but its installed capacity is relatively small in the two investigated scenarios, as limited biomass resources are rather used in other sectors that have more limited decarbonization options (e.g., transport services and petrochemical industry), as is discussed elsewhere (McCollum et al., 2014).

The dominance of solar PV during daytime is less pronounced in winter months (December–February), with solar PV generating 32% (FullTech) and 48% (NoCCS) of total electricity at midday on average during these months, compared to 42% and 59% on average during the full year and 52% and 70% during the summer months of June–August. The lower contributions from solar PV during winter are balanced by higher contributions from wind, natural gas and bio-based electricity during winter. Figures S1–S4, Supporting Information S1, offer seasonal versions of Figure 4.

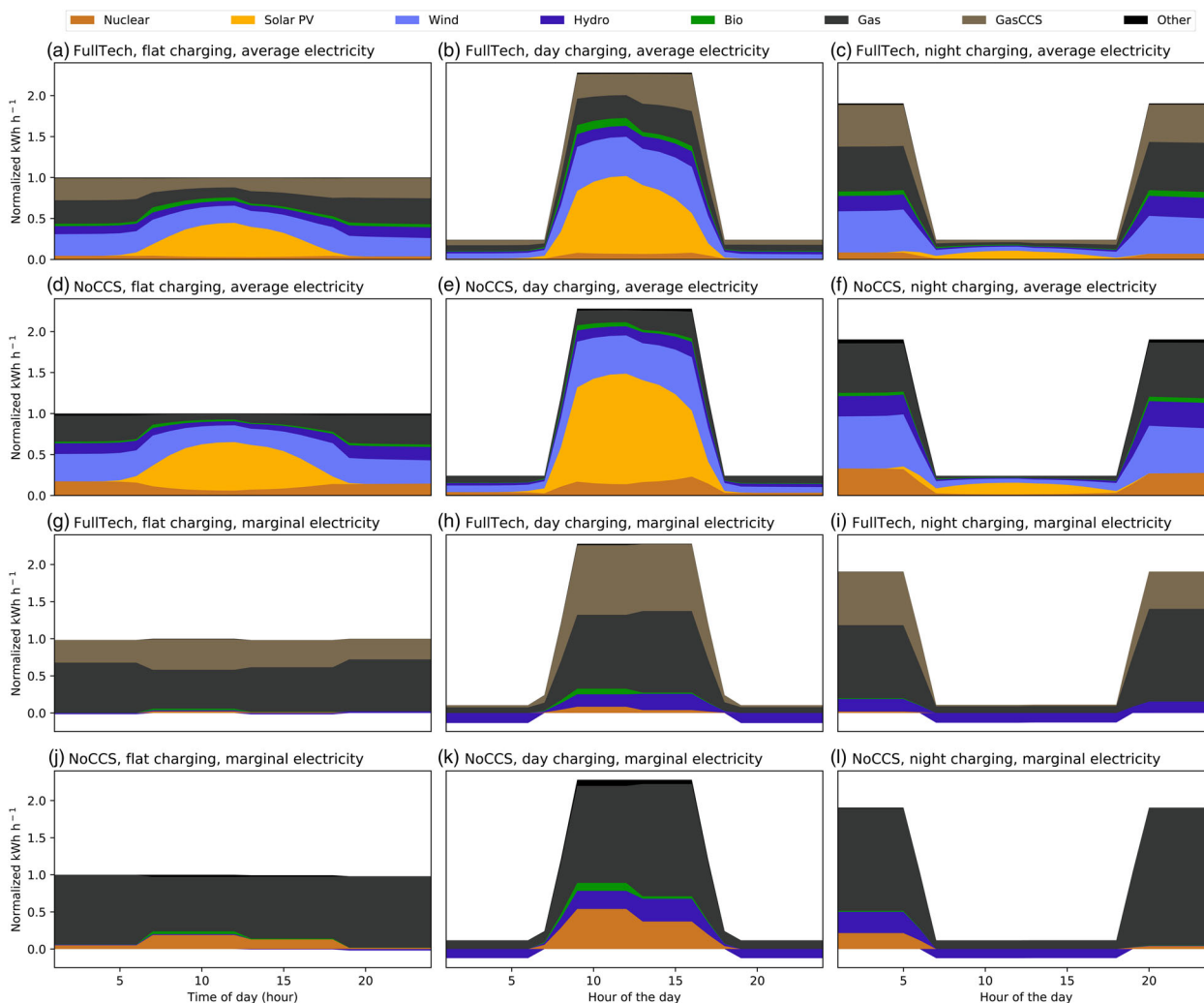


FIGURE 7 Hourly contributions to electricity production for electric vehicle charging for two scenarios (FullTech, NoCCS), three vehicle charging profiles (flat, day, night), and two electricity accounting approaches (average electricity, marginal electricity). Vertical axes are normalized to the average electric vehicle power demand across the 24-h day. Results represent a European average for an average 24-h day of the year. "Other" refers to other renewable energy sources. Underlying data used to create this figure can be found in Supporting Information S2

Owing to relatively low emission intensity of solar PV and predominance of solar PV production during daytime, the average electricity generation mix for Europe in 2050 has significantly lower emission intensity during daytime (Figure 5). This applies for both consumption-based and production-based electricity (Figures 5a and 5b, respectively). Very large variations in the emission intensities of electricity occur across individual countries due to variations in country electricity generation mixes (see 25–75% ranges in Figure 5).

The lower emission intensity of Europe-wide electricity generation during daytime, is primarily attributable to countries with medium-to-high shares of solar PV electricity generation (blue and orange lines in Figure 6). Conversely, countries with low shares of solar PV show rather constant emission intensity of electricity during day and night (green lines in Figure 6).

During late evening and night, high-penetration solar PV countries show similar emission intensity of electricity compared to that of moderate- or low-penetration solar PV countries (Figure 6). This is due to a tendency of low-, medium- and high-penetration PV countries alike to use natural gas power plants to satisfy electricity loads during late evening and night.

Supporting information S3 provides numerical values for country-specific electricity mixes with consumption-based and production-based accounting, respectively.

3.2 | Electricity demand of vehicle charging

Implementing generic time profiles for electric vehicle charging (Figure 2) into our analysis yields hourly compositions of electricity generation to satisfy electric vehicle charging demands in Europe in 2050 (Figure 7). Unsurprisingly, for the case of average (as opposed to marginal) electricity, the day charging regime makes more use of solar PV than the flat charging regime does, which in turn makes more use of solar PV than the night

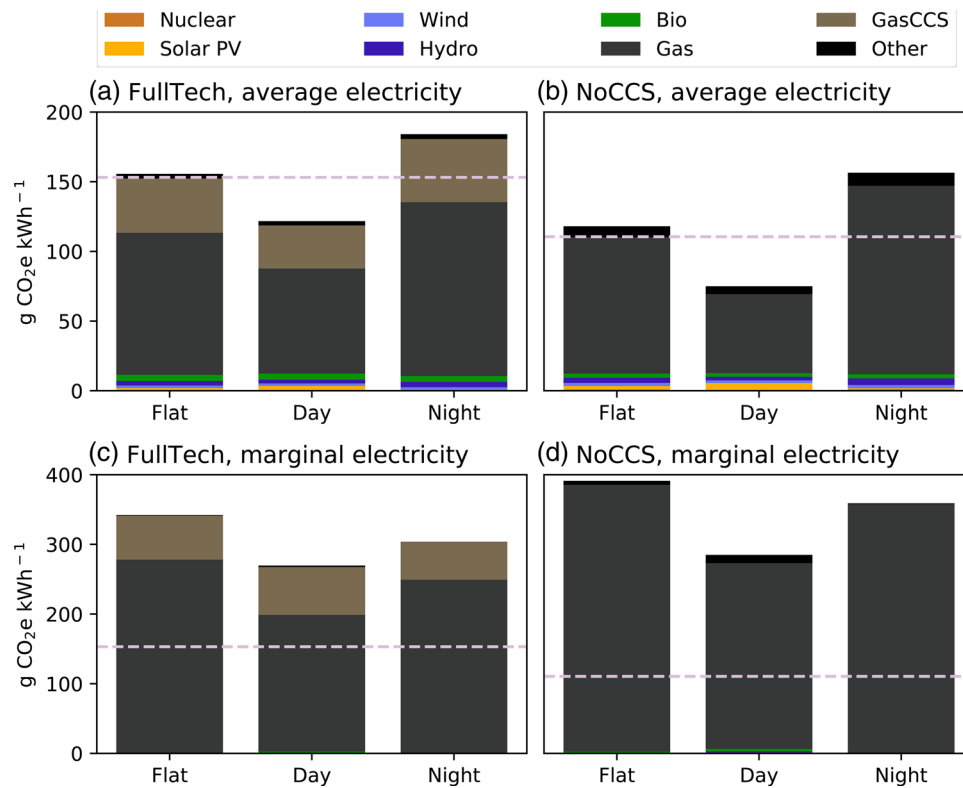


FIGURE 8 Total electric vehicle charging greenhouse gas emissions for Europe in 2050, for FullTech and NoCCS for three charging profiles (flat, day, night) broken down by electricity production technology. Note the different scales of the vertical axes. The dotted horizontal line indicates the greenhouse gas emission intensity of total average electricity consumption for Europe in 2050 (i.e., a total column height below/above the dotted line indicates better/worse performance of electric vehicles than average electricity consumption). "Other" refers to other renewable energy sources. Underlying data used to create this figure can be found in Supporting Information S2

charging regime. Conversely, night charging makes more use of fossil gas-based electricity than flat charging, which in turn makes more use of fossil gas electricity than does day charging. Overall use of wind, hydro and nuclear electricity are similar across the three charging profiles.

Looking at marginal (instead of average) electricity, the picture is different. Here, short-term marginal electricity predominantly comes from natural gas (with or without carbon capture), with variable smaller contributions from nuclear. The overall contribution from nuclear is greater in NoCCS than in FullTech, and greater with the day charging regime than with the flat or night regimes. Hydropower can have both positive and negative hourly contributions to marginal electricity due to the energy storage capability of reservoirs connected to the hydro power plants. These contributions cancel each other out when summing across the 24-h day since the total inflow of hydro is the same. This implies that the optimal intra-day scheduling of hydropower reservoir systems depends on the time profile of the added vehicle charging load: When an additional day charging load (Figure 2b) is imposed on the system, hydropower generation is higher during day and lower during night than it would have been without the additional load. In contrast, when a night charging load (Figure 2c) is imposed, hydropower generation is lower during day and higher during night than it would have been without the additional load.

Figures S1-5–S1-6, Supporting Information S1, offer seasonal (winter and summer) versions of Figure 7. Figure S1-6, Supporting Information S1, (subplots a-f) highlights the major contributions of solar PV to day charging average electricity during summer (June–August). Also, the two figures (subplots g-l) reveal that marginal electricity mixes are rather similar for the winter and summer seasons.

3.3 | Emissions of electric vehicle charging

Among the three charging profiles for electric vehicles that we analyze for Europe in year 2050, day charging shows the lowest emissions (Figure 8). Using the average electricity generation mix (Figure 8a,b), day charging causes emissions of $122 \text{ g CO}_2\text{e kWh}^{-1}$ ($19 \text{ g CO}_2\text{e km}^{-1}$) (FullTech) or $75.0 \text{ g CO}_2\text{e kWh}^{-1}$ ($12 \text{ g CO}_2\text{e km}^{-1}$) (NoCCS)⁴, which is 22% or 36% lower than for flat charging and 34% or 52% lower than for night charging. This ranking of emissions performances is logical given the distinctly lower emission intensity of electricity during daytime (Figure 5), which again

⁴ Conversions into units of $\text{g CO}_2\text{e km}^{-1}$ assume median Worldwide Harmonised Light Vehicles Test Procedure (WLTP) energy consumption of $15.5 \text{ kWh}/100 \text{ km}$ for a C-segment battery electric vehicle (comparable to VW e-Golf and Nissan Leaf), as calculated from rated WLTP consumption values available from the Electric Vehicle Database, <https://ev-database.org/>, and which includes charging losses.

is attributable to solar PV generation during daytime (Figure 4). The emission intensity of day charging is 21% and 32% lower than the emission intensity of overall average electricity consumption, for FullTech and NoCCS, respectively. Similarly, the emission intensity of night charging is 20% and 42% higher than that of average electricity consumption (Figure 8).

Similarly, when assuming short-term marginal electricity (Figure 8c,d), emissions are lowest for the day charging profile (270 g CO₂e kWh⁻¹ (42 g CO₂e km⁻¹) for FullTech and 285 g CO₂e kWh⁻¹ (44 g CO₂e km⁻¹) for NoCCS), but they are only 21% and 11% lower than flat and night charging for FullTech. The tendency for marginal emissions to be lower for day charging is attributable to increased nuclear electricity contributions to marginal electricity during daytime (Figure 7h,k).

For both scenarios and for both average and marginal electricity, natural gas (with or without carbon capture) causes nearly all of the residual electricity generation emissions (Figure 8). Short-term marginal electricity yields considerably higher emissions than average electricity (Figure 8), owing to substantial shares of natural gas in marginal electricity (Figure 7).

Finally, it is interesting to compare the FullTech and NoCCS scenarios: When calculating average electricity, NoCCS exhibits lower vehicle charging emissions than FullTech; when calculating marginal electricity, it tends to be the opposite (Figure 8). This difference stems chiefly from the different roles of natural gas without carbon capture, natural gas with carbon capture and nuclear in FullTech and NoCCS (Figure 7).

Figures S1-7–S1-10, Supporting Information S1, offer seasonal versions of Figure 8.

4 | DISCUSSION

Temporal variations in electricity mixes and demands are not taken into consideration in typical LCA studies in existing literature. However, temporal variations can be expected to become increasingly important in the future, as shares of variable renewable electricity generation to total electricity generation increases. Variations occur at different temporal scales, ranging from intra-day to seasonal to inter-year (Zeyringer et al., 2018). Some variations largely follow a cyclic pattern (e.g., intra-day and seasonal variation of solar PV electricity), others are, to a larger degree, stochastic on a daily basis but often shows seasonal patterns (e.g., wind electricity) (Sørensen, 1981).

We have conducted a computer modeling experiment, combining stylized charging profiles, scenarios from an integrated assessment model (IAM), hourly power system model (PSM) simulations, and LCA coefficients. Our analysis suggests that charging electric vehicles during daytime can produce lower emissions in countries with high shares of electricity coming from solar PV. This result is robust for average (as opposed to short-term marginal) electricity mixes, as the quantified effect of lower emission intensity of electricity during daytime is both considerable and has a clear attribution to the natural maximum of solar PV output during daytime. The result applies for all four seasons of the year, though it is less pronounced during winter months (Figures S1-7–S1-10, Supporting Information S1). The result is less robust when analyzing short-term marginal electricity, both because the quantified effect is less pronounced and because the mechanisms underlying the effect are more difficult to determine.

Given the generally lower emissions of charging during daytime based on average electricity mixes, our analysis supports the case for implementing policies that stimulate workplace charging over home charging as solar power gradually takes over more of the European power generation. With the growing interest in (nearly) Zero Emission Buildings (EU, 2018) with surplus solar PV generation, there will likely be ample opportunities for daytime workplace charging directly from local PV in the future (Sørensen et al., 2018). In addition, increased use of fast chargers in combination with new electric car sharing systems may contribute to more daytime charging in the future (Biondi et al., 2016). While we have quantified emissions associated with predefined, stylized charging patterns, low emission intensities of daytime electricity can in practice also be exploited through controlled ("smart") charging (Coignard et al., 2018; Xu et al., 2020; Wulff et al., 2020) and/or grid-level energy storage (Garcia et al., 2018; Jafari et al., 2020), which are two avenues policy makers can consider. The uncertainties and limitations of the current study—as discussed in the following paragraphs—should be borne in mind when interpreting the results. Overall, the design and operation of electricity systems are complex, and ultimately, informing policy decisions will require the cumulative evidence from multiple studies of electricity systems and vehicle charging.

Clearly, great uncertainty exists in our estimates. Some uncertainties arise from inconsistencies in input parameter values (e.g., power plant efficiencies) between the three analytic frameworks (IAM, PSM, and LCA). These inconsistencies may be eliminated in the future through more harmonization of data. Other uncertainties relate just to assumed values, such as values assumed in THEMIS for methane losses and leaks to the atmosphere from natural gas extraction and distribution (Bouman et al., 2015; Schwiertzke et al., 2016). Yet other uncertainties originate from simplifications in our model representation of future electricity systems, such as lack of consideration of increased future deployment of energy storage (Garcia et al., 2018; Jafari et al., 2020), flexible demand (Strbac, 2008), and vehicle-to-grid (Kempton & Tomić, 2005) technologies. The computations of short-term marginal electricity mixes are based on considerations of an additional electricity load due to electric vehicles without any consideration of curtailment of wind and solar production capacity (Scholz et al., 2016).

Uncertainties and variations of the life cycle emissions coefficients of electricity production (Section 2.5) are discussed extensively in previous literature that rely on the same life cycle inventory data (Arvesen, 2020; Arvesen et al., 2018; Gibon et al., 2017; Pehl et al., 2017). While individual emission coefficients can have high uncertainty, we do not expect such uncertainties to considerably affect key findings of the current study. This is because the key findings arise from the order-of-magnitude difference between the emission coefficients of fossil electricity on the one hand, and

non-fossil electricity on the other hand. We deem this order-of-magnitude difference to be much greater than the uncertainties of individual values for solar PV electricity.

Average electricity mixes are conceptually appropriate for identifying the share of total emissions that is associated with a certain electricity demand. The idea is that if one were to apply the same approach for all electricity demands, one would arrive at the total emissions associated with the electricity sector, and if one were to apply the same approach for all final products (including non-electricity products), one would arrive at total global emissions. Marginal emissions, on the other hand, are not as meaningful for identifying shares of a total; rather, their benefit is that they are estimates of how emissions change when a demand is added or removed. In this study, we analyze short-term marginal emissions. To quantify long-term marginal emissions, as in Vandepaer et al. (2018) and Vandepaer et al. (2019), it would have been necessary to also estimate the marginal added investments due to the new demand.

Stochastic variations are outside the scope of the current study, which focuses on intra-day variations that are evident as cyclic patterns over a full year. Finally, the current study portrays snapshots of a discrete point in the future (year 2050) but does not address how the timing of electricity system development and vehicle electrification compete or interplay over longer (interannual or interdecadal) timescales.

A key finding of the present study is the significant differences in the emission intensities of different electric vehicle charging profiles in scenarios for the year 2050. Hence, the emission benefits of electric vehicles depend on the timing of vehicle charging, although this is often overlooked in debates and assessments, including many LCAs and scenario assessments. There is a need for future research to further investigate the effects of time of charging on the emissions associated with electric vehicles. In general, it is also a question whether the time profiles of electricity mixes and electricity demands should be taken into consideration to a larger extent in LCAs in the future. On the one hand, given that electricity needs to be consumed at the same time as it is supplied, there is a theoretical case for adopting time-specific accounting of electricity generation mixes and electricity demands in LCA. Furthermore, in practice, such accounting would allow LCAs to identify opportunities that lie in time management strategies for electricity demand, similarly as in the current study for the case of electric vehicle charging. On the other hand, electricity is a product that is uniquely difficult to physically trace from production to user; hence, there is also a practical case for simplified treatments that only consider yearly average electricity mixes and demands.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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