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Environmental impacts of extreme fast charging

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Abstract

As electric vehicles and their associated charging infrastructure continue to evolve, there is potential to simultaneous alleviate range and recharge concerns with the development of extreme fast chargers (XFC) that can fully charge batteries in PEVs in the span of a few minutes. Recent announcements from EVSE providers and vehicle manufacturers suggest that XFC charging stations, which can recharge a BEV at roughly 20 to 25 miles per minute of charging, and XFC-capable BEVs, could be commercially available within the next 5 years. Our study investigates the potential emission impacts of widespread use of extreme fast charging (350 kW) for electric vehicles in 2030. We conduct a novel vehicle charging simulation model by combining empirical charging behavior data across several data sources. These charging demands are then added as exogenous load to the Grid Optimized Operation Dispatch (GOOD) model, which simulates the operation of generators across the Untied States. We find that XFC can increase both greenhouse gas emissions and local air pollutants, though the results are sensitive to local contexts and grid composition.

1. Introduction

Plug-in electric vehicles (PEVs) are a compelling new vehicle technology to address both oil dependency and transportation emissions. The first commercial electric vehicle was made available in the United States in 2008 and since then the market has rapidly grown to over 40 available model[1]. Sales of electric vehicles in the United States capture just over 2% of the market[2], though they have reached as high as 10% of sales in states such as California. The rapid growth of the market is expected to continue: policies such as the Zero Emissions Vehicle program continue to increase requirements for electrification for automakers[3,4], state

and regional goals for electric vehicle adoption[5], and announcements by automakers making significant commitments to electrify new vehicle models[6].

However, significant barriers to widespread electrification of the passenger transportation sector remain. One of the most common barriers related to PEVs is known as 'range anxiety', an artifact of the perceived limitation in the range of the vehicle coupled with slow recharging times (Berkeley *et al* 2018, Bonges III and Lusk 2016, Brand *et al* 2017, Cherchi 2017, Cirillo *et al* 2017, Daramy-Williams *et al* 2019, Degirmenci and Breitner 2017, Gnann *et al* 2019, Gnann *et al* 2018, Hardman *et al* 2016, Haustein and Jensen 2018, Karlsson 2017, Lane *et al* 2018, Neaimeh *et al* 2017). As PEVs and their associated charging infrastructure continue to evolve, there is potential to simultaneously alleviate range and

[1] https://www.hybridcars.com/june-2018-hybrid-cars-sales-dashboard/.
[2] https://www.greentechmedia.com/articles/read/us-electric-vehicle-sales-increase-by-81-in-2018.
[3] https://ww2.arb.ca.gov/our-work/programs/zero-emission-vehicle-program.
[4] Union of Concerned Scientists [UCS]. (2016) What is ZEV? Retrieved from https://www.ucsusa.org/clean-vehicles/california-and-western-states/what-is-zev.

[5] Governor Edmund G. Brown Jr '2018 ZEV Action Plan'. Governor's Interagency Working Group on Zero-Emission Vehicles. Retrieved from http://business.ca.gov/Portals/0/ZEV/2018-ZEV-Action-Plan-Priorities-Update.pdf.
[6] https://www.teslarati.com/automakers-come-acceptance-ev-revolution-begun/announcements/.

recharge concerns with the development of extreme fast charging (XFC) that can fully charge batteries in XFC-capable battery electric vehicles (BEVs) in the span of a few minutes. Recent announcements from electric vehicle supply equipment (EVSE) providers[7],[8], and vehicle manufacturers[9] suggest that XFC charging stations-which can recharge a BEV at roughly 20 to 25 miles per minute of charging-and XFC-capable BEVs could be commercially available within the next 5 years[10].

2. Literature review

XFC technology is relatively new with only a few existing infrastructure deployments and no commercially available vehicles that are capable of fully utilizing the high-power charging rates. Few studies have been published on XFC technology, although a thorough overview of the technology was published in a series of papers by a joint team of researchers from the Argonne National Laboratory, Idaho National Laboratory, and National Renewable Energy Laboratory. The work encompassed a review of battery technology that would be necessary to support XFC events (Ahmed *et al* 2017), the infrastructure and associated economics necessary for the technology (Burnham *et al* 2017), and the design considerations on the vehicle side and associated requirements that would enable XFC (Meintz *et al* 2017). While these studies provide a comprehensive overview of the technology and the technical requirements that may lead to successful implementation of XFC, there have not been any studies that have investigated the emissions impacts associated with the use of XFC. Our study attempts to fill this research gap.

Several methods are available to estimate the demand and subsequent generation and emissions associated with electric vehicle charging events: average emissions, marginal emissions, and consequential emissions. At the simplest level, one can assume average emissions rates associated with a kilowatt-hour (kWh) of charging. However, the average emissions approach takes a homogenous view of on-grid generation resources when, in reality, a marginal kWh of demand from a charge event will result in an increase in generation from generation resources that are used to meet marginal (i.e. not baseload) demand.

The marginal emissions approach involves estimating the emissions associated with the final quantity of demanded electricity. This approach was first demonstrated in a regression-based method (Siler-Evans *et al* 2012) and was later applied to several case studies of electric vehicle deployments to better understand the emissions associated with charging (Tamayao *et al* 2015, Yuksel and Michalek 2015, Zivin *et al* 2014, Hoehne and Chester 2016, Archsmith *et al* 2015). However, the marginal emissions approach only provides accurate estimates of emissions for studies that have a small volume of additional load (so that the marginal generating unit is not exceeded) and in current day estimates (as changes to the capacity mix would result in different marginal generators).

To better understand the implications for longer time periods or for cases with a substantial adoption of electric vehicles (or other significant alterations to the load), we must construct a detailed representation of the electricity grid from the ground up to model the dispatch behavior of the grid under different demand scenarios. Using a dispatch model allows us to employ the consequential emissions approach in which we can study the generation and emissions resulting from specifically identifiable loads that are added to the baseline load (i.e. the charging load in this analysis). This approach results in a much more detailed picture of the power generation associated with electric vehicle charging events and better highlights the nuances of charge timing, rates of charging, and the resources that are dispatched to meet the demand from charging. Marginal emissions are a subset of consequential emissions but are only able to accurately portray emissions in cases where the system does not change dramatically.

In this study, we use the consequential emissions approach to perform a bottom-up examination of consequential generation and emissions to assess the long-term impacts of XFC events. A few studies have implemented the consequential approach (Jansen *et al* 2010, Weis *et al* 2016, Melaina *et al* 2016, Sohnen *et al* 2015, Sioshansi 2012), but none have conducted systematic analyses of future scenarios of electric vehicle adoption and charging at the same scale and resolution, nor have any focused specifically on extreme fast charging events. For example, both Weis *et al* (2016), Sohnen *et al* (2015), Sioshani (2012) only consider sub-regions within the US (PJM Interconnection and California respectively). Limited regional coverage has serious implications on the validity of results as the contribution of imports and exports are difficult to introduce with accuracy exogenously. Melaina *et al* (2016) is a national model, but is a unit commitment based economic dispatch which requires a simplification of their temporal coverage. The authors consider only 17 time slices across a full year and operates at an hourly resolution. Our

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[7] https://www.greencarreports.com/news/1116 550_electrify-america-switches-on-the-first-350-kw-fast-charging-station-in-chicopee-mass.

[8] https://www.greencarreports.com/news/1120 518_evgo-launches-first-public-350-kw-fast-charger.

[9] https://www.greencarreports.com/news/1120 457_porsche-already-has-a-prototype-that-will-charge-faster-than-its-350-kw-taycan.

[10] https://www.utilitydive.com/news/15-minute-charge-for-a-300-mile-range-doe-moves-to-boost-evs/522 653/.
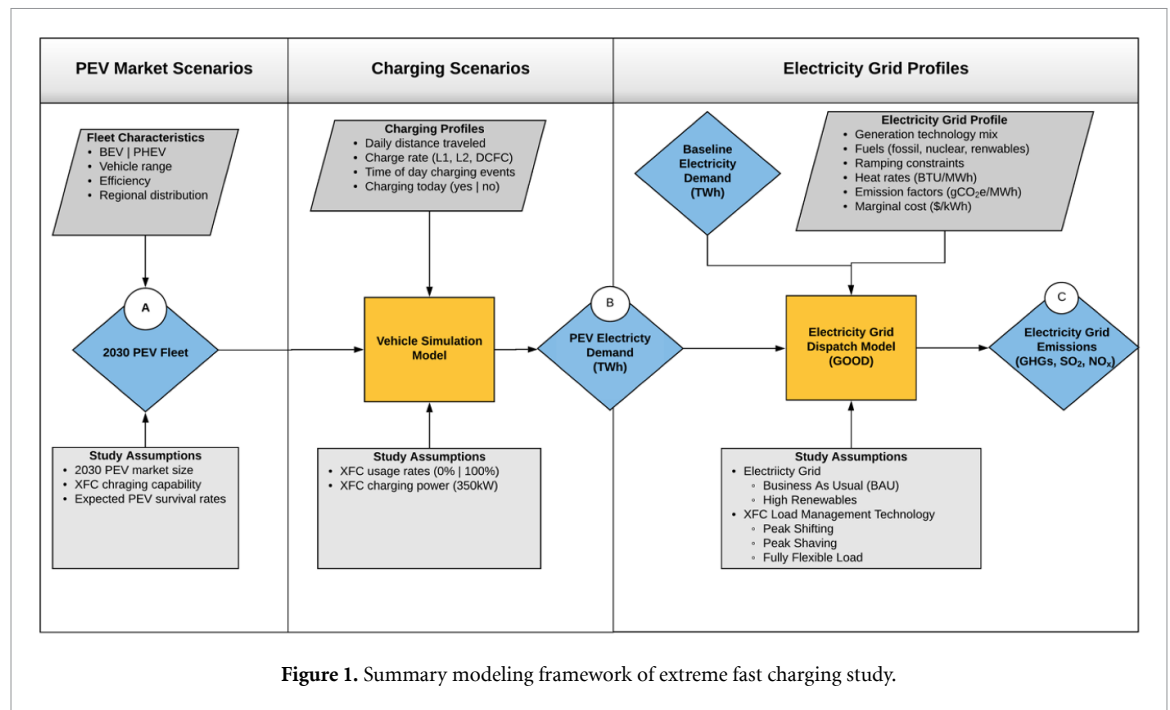
Figure 1. Summary modeling framework of extreme fast charging study.

work operates at 10-minute increments—this is a crucial distinction that allows us to represent ramping constraints of generation in response to sudden load increases that would be observed with XFC events.

3. Methods

Our modeling framework is described in figure 1. First, we define the national PEV vehicle stock (identified as A in the figure) in 2030 by technology and region. The PEV vehicle stock dataset is fed into a vehicle simulation model (VSM), which includes trip distances and charging behavior parameters, to calculate electricity demand (measured in megawatt hours [MWh]) at 10-minute time steps for the year 2030 (identified as B in the figure). Next, we employ the Grid Optimized Operation Dispatch (GOOD) model, an economic dispatch model, to simulate the operation of the U.S. electric grid given the PEV demand profiles scenarios. The GOOD model is based on detailed data on the installed generation capacity and existing baseline energy demand (non-PEV). The dispatch model then calculates the energy generation and resulting electricity grid-based emissions for all projected PEVs (identified as C in the figure) under a series of different scenarios.

Our research considers several scenarios as inputs for the modeling structure laid out in figure 1. These scenarios include two variations in the adoption of electric vehicles, two electricity grid profiles, and two charging behavior profiles of PEV owners in 2030. The XFC charging behavior includes a subset of three mitigation scenarios as shown in table 1. This scenario design is used to evaluate the incremental electricity

Table 1. Scenarios for 2030 modeling analysis. The combination of all grid, charging, and adoption scenarios results in a total of 28 scenarios, each of which is run for one week in each of four seasons. The 'None' charging scenario is necessary to establish a baseline grid simulation profile to determine consequential impacts.

Grid Scenarios	BAU		High Renewables
Charging Scenarios	None	BAU XFC	XFC w/ mitigation 1. Peak Shaving 2. Peak Shifting 3. Flexible Load
Adoption Scenarios	Low (11 million)		High (64.7 million)

demand and change in the load profile from adoption of XFC. The resulting incremental electricity demand scenarios are then fed into the GOOD electricity dispatch model to estimate the resulting emissions from the electricity generation sector for each scenario.

3.1. Vehicle Simulation Model (VSM)

The VSM uses a projection of the PEV fleet (see appendices A and B) in combination with a series of probability distributions on the number of miles traveled per day and charging behaviors to calculate electricity demand (measured in MWh) in 10-minute intervals for 2030. First, the PEV driver will decide whether or not to charge in a given day based on the charging frequency distribution with an exception that if the state-of-charge (SOC) reaches 20% or below in a given day it will always charge. As the simulations draw from real-world charging behavior, the timing of charging associated with each charging speed should be representative of the locations where charging occurs (even though we do not explicitly

simulate the location of charging). Given a charging event:

(1) The simulation will decide what rate to charge (Level 1 [L1], Level 2 [L2], or DC Fast [DCFC]) based on a charge rate distribution

(2) the simulation will decide when to charge based on a charge time distribution

(3) the simulation will decide how much the vehicle needs to charge based on how much it travels (from a vehicle travel distribution) and the vehicle efficiency

In scenarios with XFC, we assume that XFC-capable vehicles will replace all charging with XFC. For each charging event, we simulate the rate that each individual vehicle charges from a set of distributions on charging rate that depends on the technology type of the vehicle (short range vs. long range and PHEVs vs. BEVs).

3.2. Electricity Grid Modeling

We develop the Grid Optimized Operation Dispatch (GOOD) model, a type of economic dispatch model. An economic dispatch model is a method of simulating the operation of electric power-producing generator units such that it fulfills the demand of electricity at minimum cost to the system operator. The dispatch is defined as a linear optimization program that operates with respect to the following decision variables: 1) power generation from a generation unit (x^{gen}) across each generator g and time period t and 2) transmission of power (x^{trans}) from region r to region o for all time periods t. The costs associated with each decision variable are $c^{gen.cost}$ and $c^{trans.cost}$ respectively and the objective function defining the dispatch model is shown in equation (1).

$$\min \sum_{gt} x_{gt}^{gen} c_g^{gen.cost} + \sum_{rto} x_{rto}^{trans} c_{ro}^{trans.cost} \text{wrt} : x_{gt}^{gen}, x_{rto}^{trans}$$

In general, the model dispatches generating units according to the lowest marginal cost given cross region bulk transmission constraints. This implies that in most instances renewable and nuclear energy with close to zero marginal cost are always dispatched first. Thus, any incremental demand or load shifting primarily impacts the grid's natural gas and/or coal consumption. In addition to the objective function of the linear system, there are constraints that comprise the dispatch model and operate at various levels of regions and time periods (see appendix E). Note that the GOOD model is not a capacity expansion model: it does not endogenize the installation of new generators, instead we assume grid expansion as an exogenous input. This can result in a slightly different grid mix if generation assets were selected to specifically handle load increases resulting from electric vehicle loads.

One of the primary outcomes of interest is how power generation responds specifically to electric vehicle charging events. To isolate this outcome (as electrons cannot be tracked in our model), we run every grid scenario against a baseline with no electric vehicle charging demand. This baseline can be subtracted away from the generation results to provide the 'consequential' generation-that is the operation of power generators that are specifically responding to electric vehicle charging events.

3.3. Modeling scenarios overview

Our modeling framework defines a variety of scenarios combining dimensions of different vehicle charging time profiles with different future states of the world related to vehicle adoption and renewable growth on the electric grid. We examine five specific vehicle charging scenarios that vary in terms of the time of day when PEV charging demand draws from the grid:

- Business-as-usual (BAU) where most vehicles charge at night
- XFC where vehicle charging has predominately shifted to daytime
- XFC scenarios with mitigation
  - XFC with peak shifting mitigation
  - XFC with peak shaving mitigation
  - XFC with fully flexible load.

The XFC scenario, as well as the XFC mitigation scenarios, assumes a certain charging behavior, since there is a lack of data on real-world behavioral charging patterns related to XFC. We assume that all vehicles capable of charging with XFC will replace all other charging levels with XFC (essentially reverting to a gas station model). We assume that the charging occurs with the same timing distribution as DCFC. Because this is a prospective analysis with uncertainty about the future, the different charging scenarios are modeled under several potentially different states of the world in 2030:
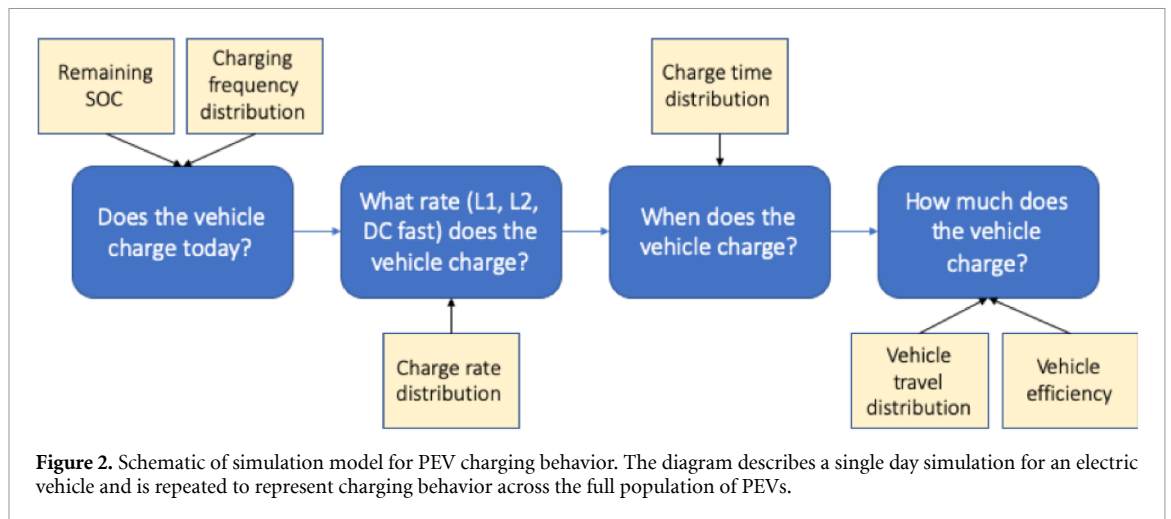
- Two projections of vehicle adoption are used in the model run
- Two scenarios of the share of renewables on the electricity grid and used in the model runs

Across all combinations of the scenarios and future states of the world, we run a total of 20 modeled scenarios across four representative weeks of the year (in each season). Additional detail on the three XFC mitigation scenarios are described in the appendix.

4. Results

4.1. Electricity Dispatch Generation

The primary outputs of the GOOD model describe how the generation is dispatched to meet total load.

Figure 2. Schematic of simulation model for PEV charging behavior. The diagram describes a single day simulation for an electric vehicle and is repeated to represent charging behavior across the full population of PEVs.

We are specifically able to identify the 'consequential' generation related to charging events by running dispatch models with no charging demand for PEVs and subtracting from each of the charging scenarios. The consequential generation then describes how power-producing generators are deployed specifically to meet demand of the PEV charging events. In figure 3, we provide the annual breakdown of generation by fuel type given low and high adoption of PEVs, respectively. These figures also show the difference between the baseline and the high renewable grid.

Generally, under the baseline grid scenario, about one-fourth of consequential generation is met through coal power and the remainder comes from natural gas. This is due to the fact that lower variable cost power (such as electricity from renewables or nuclear power) has already been dispatched to provide electricity to meet non-PEV electricity demand. However, this amount decreases under the flexible load mitigation scenarios, ranging from an 11% decrease (high adoption) to a 36% decrease (low adoption) in coal utilization. In the high renewable grid, we observe a decrease in coal utilization of 47% (high adoption) up to 57% (low adoption) as vehicles are better able to take advantage of curtailed renewables. The mitigation scenarios of peak shaving and peak shifting do not result in substantially different proportional dispatch of renewables compared to the XFC case without mitigation.

We provide an overview of consequential generation over the course of one week for select scenarios in figure 4. While coal plants are actively being retired over the next decade, we still observe coal being dispatched on the margin in certain regions at specific times of day. As the electricity mix of the grid shifts away from coal generation, we observe a shift in both imports and exports of electricity to meet load demand. Additionally, for scenarios that consider smart charging, demand is shifted in order to take advantage of cheaper generation–typically natural gas replacing coal or in the case of high

renewables a shift to solar and wind. In the first scenario, generation is provided to meet BAU charging demand-primarily home charging supplemented by public L2 and DCFC events. The load demand follows a regular pattern with peaks in the evening. However, the consequential generation used to meet the charging demand is slightly more variable at the sub-hourly level because of the underlying variability of the baseload electricity demand, which ultimately affects the generators dispatched to meet the charging load. Consistent with figure 3, the load is met primarily with natural gas alongside a smaller dispatch of coal generation. We do not observe any load being met with lower emission-generation sources such as renewables or nuclear because the capacity is already used to meet the baseload demand.

In the second and third scenarios, the charging load is XFC without any mitigation technologies. The load is met by a baseline grid and a high renewable grid scenario respectively. The load shape differs slightly from the BAU scenario, with three different peaks occurring throughout the day (as opposed to nighttime peaks in the BAU case). The peaks are associated with morning, noon, and early evening hours of the day. In the BAU charging scenario, the proportion of coal dispatched to meet the load is slightly lower than in the XFC scenario. In addition, the variability of the consequential natural gas generation is considerably higher than in the BAU case-indicating that flexibly dispatchable resources (such as natural gas) are likely needed to support XFC events. The third scenario is identical with the exception of the additional renewable resources on the grid. The capacity is high enough that there is a fair amount of renewable curtailment occurring in the absence of electric vehicle charging load, which is why it appears in the consequential generation. However, despite the 30% increase in renewables in the high renewable grid scenario, this source remains relatively modest at only about 5% of the generation for XFC due to
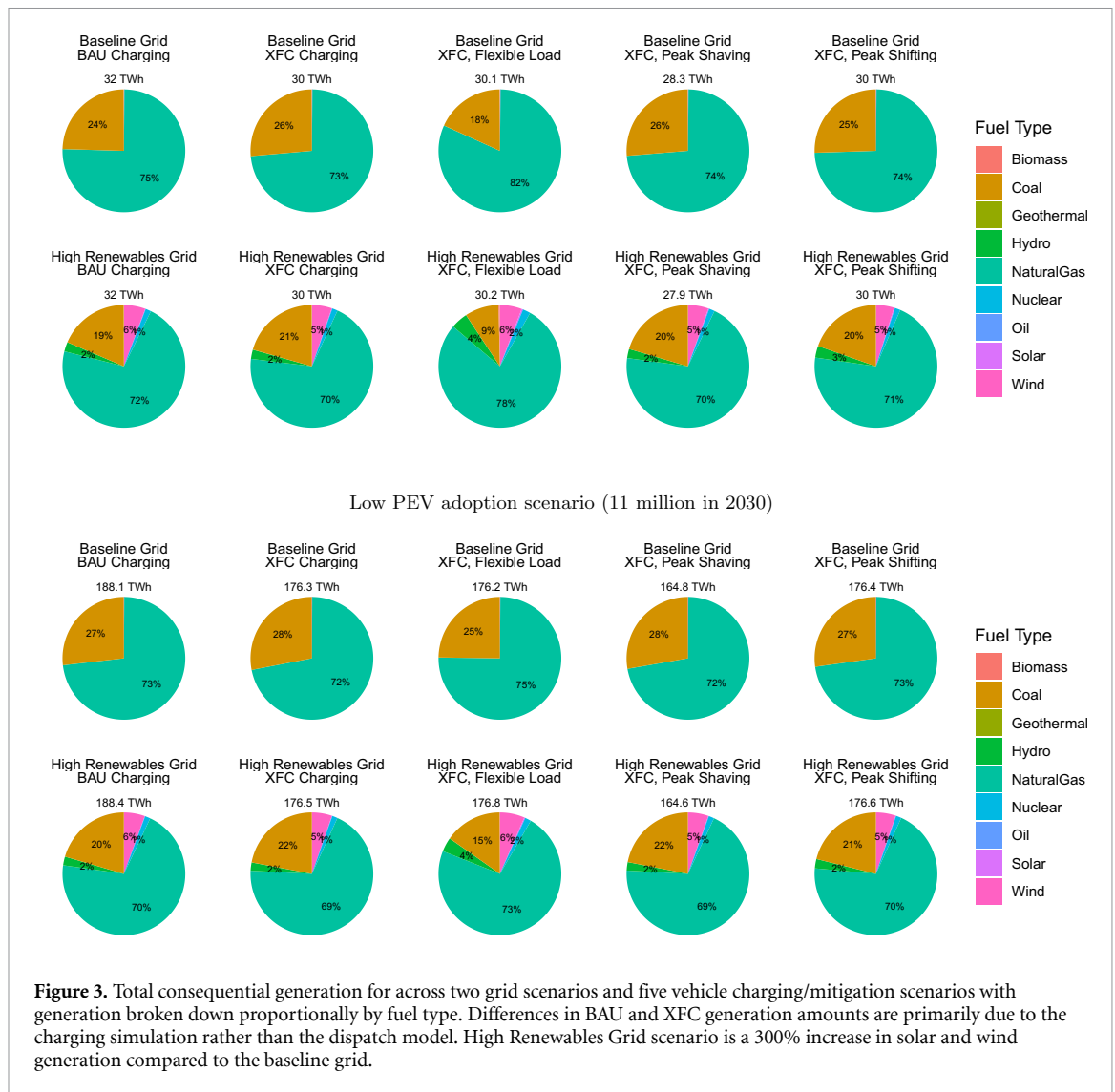
Figure 3. Total consequential generation for across two grid scenarios and five vehicle charging/mitigation scenarios with generation broken down proportionally by fuel type. Differences in BAU and XFC generation amounts are primarily due to the charging simulation rather than the dispatch model. High Renewables Grid scenario is a 300% increase in solar and wind generation compared to the baseline grid.

transmission being fully saturated where renewable resources are located.

We also consider the mitigation scenarios of peak shifting, peak shaving, and fully flexible load in the fourth, fifth, and sixth subplots of figure 4. In the peak shifting scenario, the threshold cutoff constraint is met. Load above the threshold is shifted from peak hours (which occur in the daytime), creating a flat region of load for when the load would have exceeded the threshold. The charging load is shifted to non-peak (nighttime) hours, leading to a slight decrease in coal generation compared to corresponding scenarios without mitigation. This mitigation consistently decreases the consequential generation of coal by about 1% of the total (see table 2). In the load shave scenario, we remove the load entirely, assuming that locally renewable sources are able to fully charge the battery and preventing the charging load from exceeding the threshold. This decreases the overall charging demand that we add to the GOOD model. Over a full year, in a low PEV adoption scenario, peak shaving decreases demand by about 6%

(a 1.7 terrawatt hour (TWh) decrease) while in the high PEV adoption scenario this decreases demand by about 7% (a 11.6 TWh decrease).

The fully flexible mitigation scenario allows our model to endogenously determine the optimal period to charge the vehicle. We observe that the pattern of charging load changes quite dramatically compared to all other scenarios, shifting nearly all the load to nighttime hours. While all other charging scenarios have vehicles charging throughout the day, the fully flexible scenario completely shifts the load to certain hours of the day leading to much higher peaks (15-25 gigawatts [GW]) compared to other scenarios (3-5 GW). This shift allows for a much higher utilization of natural gas generation, we also observe this in figure 3 as the proportion of coal generation shrinks by 9% and 10% respectively.

The overview of consequential generation spanning a week of demand from electric vehicle charging provides important insights into the potential for how loads can be shifted and the resulting impacts on generation. Regardless of the time of charging, no

Figure 4. One week of GOOD model dispatch results for low PEV adoption during the summer.
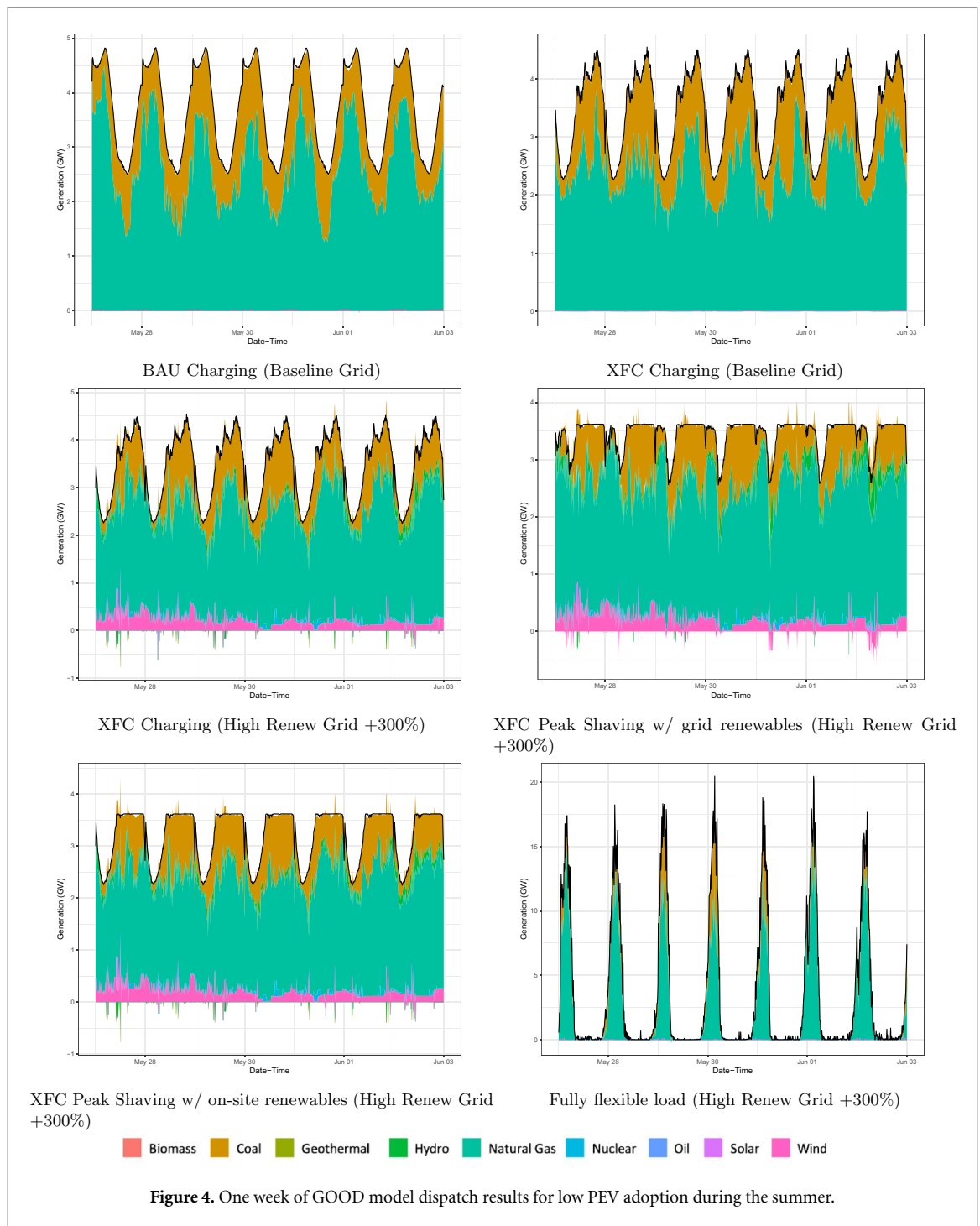
renewables are dispatched to meet charging demand in the baseline electricity grid. This is because low carbon generation sources are dispatched first to meet baseload demand, the GOOD model then assigns a combination of natural gas and coal plants to provide power for charging demand. As the load shape changes across different charging demand scenarios, the GOOD model changes the dispatch of generating units used to meet the load.

This changes under the high renewable grid where some curtailment of renewables occurs due to the excess of supply. As a result, the additional consequential electric vehicle demand can utilize these remaining renewables, as high as 5% of the demand on average is met by these renewable sources.

4.2. Emissions impacts
The annual continental U.S. consequential emissions and emission rates per unit of generation were calculated in 2030 associated with charging demand for each of our scenarios. Our model considers five pollutants: CO_2, CH_4, NO_x, N_2O, and SO_2. The source of these emissions is primarily from natural gas and coal power plants that are dispatched to provide electricity for charging PEV batteries or on-site storage for XFC mitigation scenarios. Due to the mix of generation
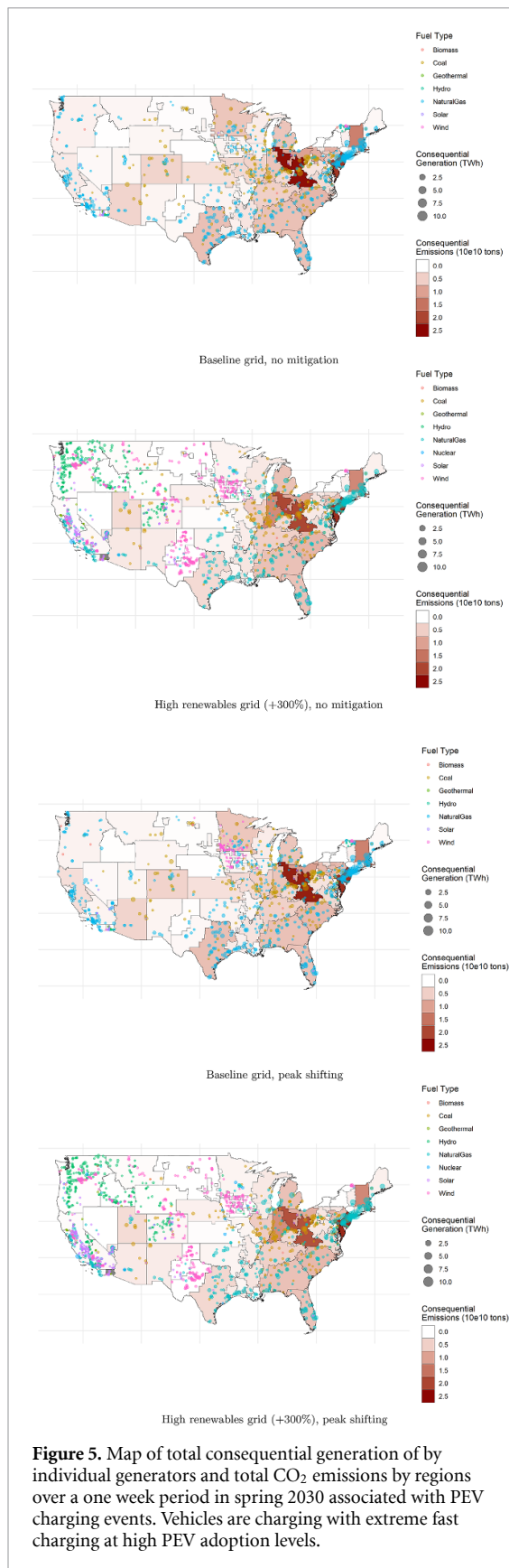
Figure 5. Map of total consequential generation of by individual generators and total CO_2 emissions by regions over a one week period in spring 2030 associated with PEV charging events. Vehicles are charging with extreme fast charging at high PEV adoption levels.

emissions rate (1.26 tons of CO_2 per TWh) than the XFC scenario emissions rate (1.29 tons of CO_2 per TWh). This is due to the higher proportion of coal generation in the XFC scenario compared to the BAU scenario. In terms of emissions, all pollutants are higher under XFC scenarios and XFC mitigation scenarios than BAU charging with the exception of the flexible load mitigation scenario. While most of the increases are relatively small, SO_2 emission rates are approximately 6% to 14% higher under the XFC charging scenarios. The primary reason for the increase in emissions is a shift towards daytime charging events, leading to an increase in deployment of coal generation. The relatively higher average price of coal leads to those generation units being more common during daytime peaks (since much of the natural gas generation has already been dispatched for baseload generation). The peak shaving and shifting mitigation scenarios were not appreciably different from the no-mitigation XFC scenario for CO_2 emissions. However, emissions rates for criteria pollutants tended to be marginally better under the mitigation scenarios than the no-mitigation XFC scenario. In general, though, the results tend to be very similar. Note that in addition to emissions rates changes across scenarios, we are also able to measure the changes in total emissions. While some of our findings are confounded by variation in the total charging demand in different scenarios, we were able to observe comparable emissions differences where load demand was consistent in the XFC and its corresponding mitigation scenarios. In this case, we observe emissions savings in peak shaving (which essentially removes load in the same manner as behind-the-meter). Under low adoption scenarios, there is about a 2 Mton reduction in CO_2 in the peak shave mitigation compared to XFC without mitigation while this reduction increases to 16 Mton reduction in CO_2 under high adoption scenarios.

The fully flexible storage mitigation scenario emissions differ substantially from the other charging scenarios. With the exception of CO_2, all other pollutant emission rates decrease in the BAU grid scenarios: CH_4 by 22% to 35%, NO_x by 7% to 15%, N_2O by 24% to 38%, and SO_2 by 40% to 48%. Completely shifting the XFC charging from daytime to lower cost natural gas generation during the nighttime has a large side effect of improving many of the local pollutants associated with coal generation. Additionally, in the high renewables case for XFC with flexible load mitigation, the CO_2 emissions are lower than the BAU charging scenario because the local storage can also take advantage of additional curtailed renewables.

In figure 5, we provide a regional breakdown of the consequential emissions as well as the plant-level consequential generation by fuel type. These maps provide a quick comparison of the regional differences in consequential generation and emissions

sources, the emissions of each pollutant do not necessarily correlate directly with the amount of generation in a given scenario.

Table 2 shows the emissions rates per TWh for each scenario. The BAU scenario has a lower

Table 2. Summary of consequential and emissions rates by scenario and pollutant.

Adoption	Charging	Baseline Grid						High Renewables Grid (+30%)						High Renewables Grid (+300%)					
		CO_2 [Mtons /TWh]	CH_4 [MTons /TWh]	NO_x [kTons /TWh]	N_2O [MTons /TWh]	SO_2 [kTons /TWh]	CO_2 [MTons /TWh]	CH_4 [MTons /TWh]	NO_x [kTons /TWh]	N_2O [MTons /TWh]	SO_2 [kTons /TWh]	CO_2 [MTons /TWh]	CH_4 [MTons /TWh]	NO_x [kTons /TWh]	N_2O [MTons /TWh]	SO_2 [ktons /TWh]
Low PEV	BAU	1.26	0.153	0.603	0.0213	0.988	1.26	0.151	0.584	0.0209	0.916	1.1	0.118	0.513	0.0163	0.731
	XFC	1.29	0.162	0.65	0.0227	1.1	1.28	0.16	0.627	0.0223	1.03	1.13	0.127	0.557	0.0177	0.833
	XFC, Peak Shave	1.29	0.162	0.647	0.023	1.09	1.28	0.159	0.62	0.0222	1.01	1.12	0.127	0.555	0.0177	0.823
	XFC, Peak Shift	1.28	0.158	0.627	0.022	1.05	1.27	0.155	0.61	0.0217	0.97	1.11	0.123	0.537	0.017	0.787
	XFC, Flexible	1.28	0.126	0.551	0.0173	0.658	1.27	0.126	0.586	0.0172	0.675	0.974	0.0825	0.517	0.0109	0.437
High PEV	BAU	1.3	0.164	0.648	0.0231	1.1	1.29	0.161	0.623	0.0225	1.03	1.13	0.126	0.541	0.0176	0.794
	XFC	1.32	0.172	0.702	0.0242	1.19	1.31	0.168	0.67	0.0237	1.12	1.16	0.135	0.578	0.0188	0.884
	XFC, Peak Shave	1.32	0.17	0.689	0.024	1.17	1.3	0.167	0.66	0.0235	1.1	1.15	0.133	0.572	0.0186	0.87
	XFC, Peak Shift	1.32	0.167	0.683	0.0236	1.13	1.31	0.164	0.653	0.023	1.07	1.14	0.13	0.561	0.0181	0.84
	XFC, Flexible	1.28	0.154	0.578	0.0215	0.936	1.26	0.149	0.561	0.0207	0.904	1.03	0.101	0.476	0.0138	0.565

across different regions for a several scenarios. The magnitude of emissions is provided on the same scale across all the maps, but the generation has a distinct scale in each map so that the relative amounts within each scenario are more visible. The total consequential generation is a small fraction of total generation, even at extremely high levels of electric vehicle adoption the total annual demand is only about 190 TWh in comparison to the total 4,200 TWh generated annually for baseload demand.

Almost all the consequential generation in baseline grids are coming from coal and natural gas generation because the majority of cleaner sources such as solar, wind, and nuclear are dispatched first to meet the baseload demand for electricity. The western half of the United States has noticeably lower emissions than the eastern half due to the prevalence of coal power consequential generation used to meet charging load in the latter region. The highest level of emissions to be in the New Jersey, West Virginia, Ohio, and Indiana areas.

A comparison of the baseline grids and high renewables grids reveals substantially different consequential generation mix, though most of these benefits are seen to accrue in the western half of the United States. The presence of abundant renewable resources (particularly solar in California and wind in the Midwest) also frees up previously dispatched hydro power in the Pacific Northwest to provide consequential generation for charging events in the region. A substantially larger number of smaller renewable generators are dispatched to meet the load demand (as opposed to several larger fossil plants in the baseline grid scenario). There is still not any appreciable dispatch of consequential renewable generation on the east coast, though the MISO region of the Midwest does have a substantial amount of wind power. The CO_2 emissions are notably lower across the entire country, with much of the west coast nearly reaching zero emissions and the aforementioned high emissions regions in New Jersey, West Virginia, Ohio, and Indiana decreasing CO_2 by 20%. When mitigation scenarios are employed, there is a slight decrease in system-wide emissions. The shift in charging load demand through storage in the peak shifting allows for the dispatch of unused wind resources in the MISO region to meet charging load demand.

5. Discussion and conclusions

As electric vehicles continue to grow in popularity, the concept of extreme fast charging (XFC) as a means to overcome range anxiety and lessen charging time is an increasingly popular subject. However, it is largely unknown what implications XFC stations may have on the economics of charging, the electricity grid, and the emissions resulting from charging. This work is a first attempt at conducting a bounding analysis of the emissions impacts of XFC at a system level through

a series of 2030 scenarios that model different patterns of charging by PEVs, and future uncertainty in the composition of the electric grid and in the rate of adoption of electric vehicles.

This study also introduces a novel approach to modeling charging behavior. The traditional approach for estimating aggregate charging demand has been to assume charging patterns based on travel demand profiles, specifically correlated with arrival times at home and work (Wood *et al* 2017, Sheppard *et al* 2017). In this study, we employ real data on charging behavior and simulate charging from a series of empirical distributions related to the frequency, timing, and rate of charging. As real-world data on charging patterns becomes increasingly available, it will be critical to continue comparing modeled assumptions against empirical data.

The total emissions in our results are partly influenced by variation in total charging demand resulting from the Vehicle Simulation Model. This led to slightly higher load demand in the BAU charging scenario compared to the XFC charging scenario despite having an identical quantity of adopted EVs. However, our analysis finds that emission rates for key pollutants (CO_2, CH_4, N_2O, NO_x, SO_2) increases with the introduction of XFC charging (table 2). This is due to a shift from natural gas to coal-fired generation as PEV charging times shift from nighttime to daytime. This increase in emission rates holds for both the low and high PEV adoption scenarios. The increase in emission rates associated with XFC also holds as the grid moves to a higher share of renewables. Under the 300% increase in renewables that was modeled in high renewables scenarios, overall emission rates decrease as some renewables are used for XFC charging in BAU and other scenarios. However, under this high renewable grid scenario, the shift from BAU to XFC charging still led to an increase in emission rates for all pollutants modeled.

As one of the first studies to examine the impacts of XFC implementation, there are several limitations of our data and modeling approach that could be improved in future work. First, the charging simulation model takes a different approach from most other charging behavior models. Rather than drawing on assumptions of behavior, it uses empirically observed charging data. However, these data may represent early adopter behavior, which may change over time. Additionally, some of the charging distribution data such as those derived from Chargepoint or EVGo charging points include fleet vehicles (i.e. vehicles driven for transportation network companies such as Uber, Lyft, or Maven), which are not explicitly considered in our modeling efforts. The vast majority of our distributions are also drawn from California-specific charging data-the charging behavior of drivers in other regions of the country may differ, particularly in colder regions where the temperature may dictate a charging requirement that is

different than more temperate climates such as California.

The implementation of XFC in our model may also be too optimistic in the charging rates as it relates to power demand: there is no efficiency penalty for charging at higher power, which may not reflect the physical losses in reality. If XFC charging efficiency penalties are included, this could lead to increased total emissions but would likely have negligible impacts on overall emission rates. For the XFC mitigation scenarios, there is a slight disconnect in our system-level analysis compared to station-level mitigation measures. While our approach attempts to reflect this by focusing on the charging demand peak (instead of the total demand peak), the mitigation measures that station owners may take could be significantly more nuanced. On the one hand, station operators will care about charging peak to the extent that it will result in demand charges that impact the profitability of their business. On the other hand, utilities structure electricity prices to reflect system-level cost of service and to manage grid demand peak , which may or may not coincide with charging peak. Second, station operators have many more options for mitigating peaks than the implementation of storage and renewables, including slowing charging speeds temporarily or imposing real-time pricing that reflects the cost of providing a charge during a high demand period.

More research is also needed to further understand the business case for XFC charging stations, which would in turn help us understand the costs and incentives stations owners will face. Market forces and cost minimization will be the drivers of station-level load shifting or storage investments. Incentives for mitigation will vary depending on urban versus highway station settings. A cost benefit analysis at the XFC station level would help determine if government subsidies or grid investments are needed to meet emissions objectives. Some studies have begun to explore these topics (Francfort *et al* 2017), but further research is needed.

Additional research questions that extend beyond this study's objectives, but are relevant for XFC emissions impacts, include analysis of XFC's impact on the overall rate of PEV adoption:

- How important is XFC infrastructure to incentivizing EV adoption? Future work is needed to better understand the relationship between XFC charging infrastructure and consumers' willingness to switch to EVs in the future.
- If XFC is critical to broader adoption, then what is the most effective way to expand XFC infrastructure to maximize the adoption of EVs? For example, interstate corridors may provide for longer range trips, whereas expansion around daily commuting patterns may have a great

impact on adoption, since the majority of passenger vehicle miles traveled are associated with daily commutes to work or for other local destinations.

- What are the technical and/or economic barriers in the electricity distribution infrastructure that may hamper rollout of XFC infrastructure?
- What policies or regulations can lower the barriers to XFC expansion?

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments

Appendix A. Vehicle fleet assumptions

We developed a fleet projection tool to estimate the total fleet of plug-in vehicles in 2030 for our low and high PEV adoption cases, as well as the share of those vehicles that are capable of XFC. The fleet projection model uses the same five BEV and plug-in/hybrid electric vehicle (PHEV) types as in the Energy Information Administration's 2018 Annual Energy Outlook (AEO 2018) and the relative mix of these vehicles is designed to match the shares in the AEO Reference Case for 2030. The vehicle projection tool starts with PEV sales data between 2010 and 2016[11], projected annual sales from AEO 2018, and the typical lifetime of passenger vehicles[12]. The annual sales of electric vehicles are allocated from AEO regions to our grid regions on the basis of population. The electric vehicles are tracked over time based on a stock-turnover model that tracks when vehicles retire from the system. The electric vehicle

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[11]Historical sales of EVs come from the Argonne National Laboratory's *Light Duty Electric Drive Vehicles Monthly Sales Updates*: http://www.anl.gov/energy-systems/project/light-duty-electric-drive-vehicles-monthly-sales-updates.

[12]Vehicle survival rates were calculated using a Weibull distribution based on parameters obtained from (Oguchi and Fuse 2015). In the United States, the average lifespan is 16.2 years with a shape parameter of 2.8 and coefficient of determination (R^2) of 0.92.

Table A1. 2030 Fleet Summary table: Low PEV Adoption Scenario (millions).

Vehicle Type	No XFC	XFC-able	Total	Share, %
BEV100	0.2	1.3	1.6	14
BEV200	0.2	3.0	3.3	29
BEV300	0.2	3.7	3.9	34
PHEV10	1.5	–	1.5	13
PHEV20	0.0	–	0.0	0
PHEV40	1.0	–	1.0	9
Total	3.1	8.1	11.2	100

Table A2. Summary of fleet characteristics by vehicle adoption scenario.

	2030 Low PEV Adoption	2030 High PEV Adoption
Total		
# of PEVs	11 M	64.7 M
BEV/PHEV		
split	78%/22%	78%/22%
# XFC-able PEVs	8.1 M	
on-road		
(72%)		46.9 M
(72%)		

Table A3. Fuel efficiency assumptions for 2030[14].

Vehicle Type	Electric Efficiency (Wh/100 mi)	Electric Efficiency (MPGe)
BEV100	269.12	125
BEV200	280.18	120
BEV300	291.96	115
PHEV10	320	105
PHEV20	320	105
PHEV40	320	105

projections are divided into several technology categories: short-range BEVs (100 mile range), two types of long-range BEVs (200 and 300 mile range), short-range PHEVs (below 25 mile range), and long-range PHEVs (greater than 40 mile range). Several recent studies (Miele *et al* 2020, Greene *et al* 2020) have demonstrated the influence of charging infrastructure on adoption of electric vehicles. Given that our projections of electric vehicles are exogenous, we assume that the required charging infrastructure will be built to meet the necessary charging demand (and to induce adoption).

The total number of PEVs is assumed to be approximately six times larger in the high PEV adoption scenario. This adoption scenario is intended to model an extreme case of PEV vehicle adoption to represent a ceiling or bookend in the potential changes of the grid-based emissions. We assume that the vehicle mix is the same under both the low and high adoption scenarios. We assume that all three BEV vehicle types will be capable of XFC starting in 2021, while PHEV models will never be XFC capable. Table A2 presents the fleet summary data by adoption scenario.

We use the fleet projection tool to track vehicles by year of sale, allowing us to calculate the number of vehicles in the fleet that are XFC capable in 2030. For example, new BEV vehicle sales between 2021 and 2030 are projected to be 8.4 million in our low adoption scenario. By 2030, approximately 300,000 of these are assumed to be retired or no longer in operation. The remaining 8.1 million vehicles sold between 2021 and 2030 are XFC-capable BEVs still in use in 2030. Table A1 shows the fleet breakdown by vehicle type and XFC capability.

The VSM assumes fuel efficiencies for each vehicle type based on the Autonomie model[13]; 2020 lab year values (reflecting 2025 model year vehicles) were used and assumed to represent on-road averages in 2030. Developed by the Argonne National Lab System Modeling and Control Group and General Motors, the Autonomie model is a simulation tool for vehicle

energy consumption and performance analysis. Note that values were calculated rather than taken directly from the Autonomie model. For our purposes, we chose fuel economy values for midsize vehicles to represent an average value associated with a diverse fleet of compact and midsize cars, SUVs, and pickup trucks. Autonomie also estimates the fuel economy for different potential futures where technological change has improved fuel economy more aggressively. For our purposes, we use the 'average uncertainty' case in Autonomie, which is aligned with original equipment manufacturers' improvements based on existing regulations. Table presents the fuel economy values by vehicle type in both Watt hours (Wh) per 100 miles and the mile per gallon gasoline equivalents (MPGe).

Autonomie provides fuel economy estimates for PHEV25, PHEV40, and PHEV50 vehicles. We chose to use the PHEV40 for every vehicle type because the PHEV25 modeled in Autonomie contains a different engine type, and the PHEV50 fuel economy estimate does not match vehicle types in our model.

The regional distribution of the PEV stock was determined using a two-step process. First, we used the AEO 2018 regional sales for nine of their census regions (excluding Hawaii and Alaska because they are not interconnected with the continental US grid being modeled). The regional sales were then further divided into the 61 regions defined in the Integrated Planning Model (IPM has 64 regions; for simplification, we collapsed four regions: ERCOT Tenaska Frontier Generating Station (ERCOT_FRNT), ERCOT Tenaska Gateway Generating Station (ERCOT_GWAY), MISO Lower Michigan (MISO_LMI), and SPP Kiamichi Energy

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[13]https://www.autonomie.net/publications/fuel_economy_report.html. (See 'Results per vehicle' under the 2018 Report Download heading. Within the spreadsheet, see BEV tab and PHEV&BEV table).

Facility (SPP_KIAM).) by corresponding population distributions (using 2015 population data). The PEV distribution in terms of BEV versus PHEV and range categories are held constant across the regions.

Appendix B. Vehicle simulation modeling

Under the BAU charging scenario, we assume that all BEVs purchases after 2021 are XFC capable, but it is assumed that nighttime charging behavior via Level 1 and 2 rates are still the dominant behavior. Also, whereas XFC events are not observed in the CVRP survey data because XFC is not yet available, it is assumed that DCFC charges (at 50 kW) from vehicles after 2020 all switch to XFC (i.e. only older BEVs that are not XFC capable continue using DCFC). Under the XFC scenarios, the probability of charging by charge level shifts due to our assumption that all vehicles in the stock in 2030 that are XFC capable will choose XFC every time. Therefore, only vehicles that are not XFC capable charge at L1, L2, and DCFC under the XFC scenarios.

The time of day that vehicles are charged is broken down by charging speed types. For the XFC scenarios, we assume the DCFC charge time distribution represents both DCFC events and XFC charging events). The final distributions combine three datasets: Idaho National Labs for L1/L2 home-charging events, ChargePoint for L1/L2 public-charging events, and EVGo for DCFC events. We assume 85% of charging occurs at home while 15% of charging happens in public under the BAU scenario. Our assumption is based on data from the PHEV Center cohort survey, though this falls in line with other studies such as the joint National Renewable Energy Laboratory and California Energy Commission report (Bedir *et al* 2018). As mentioned previously, the XFC scenario (and corresponding mitigation scenarios) contains no home charging for any XFC-capable vehicle.

The daily travel pattern of vehicles in our simulation are drawn from the 2017 National Household Travel Survey (NHTS). While comparisons of travel distributions of current electric vehicles may differ, given a forecast to 2030 where PEV use is extended beyond early adopters, we assume that PEV driving behavior will more closely resemble the average population profile rather than the distributions of current PEV travel behavior. Our assumption therefore ensures that a switch to electric vehicle use does not alter current mobility requirements.

An overview of the sources of data and probability distributions are presented in table B4. These data sources are described in more detail in the following subsections. Although the empirical data provide a novel approach to modeling charging behavior, the data also present challenges, such as how well it represents the population of PEV drivers as a whole and whether or not it can be extended to represent future populations of PEV drivers.

Table B4. Data sources for probability distributions in charging simulation.

Data Source	Data Use for VSM
UC Davis PH&EV Center Cohort Survey	Charging frequency distribution
UC Davis PH&EV Center Cohort Survey Public charging: EVGo and Chargepoint Home charging: Idaho National Laboratory	Charge rate distribution
	Charge time distribution
National Household Transportation Survey 2017	Vehicle travel distribution

The Plug-in Hybrid Electric Vehicle (PHEV) Center, part of the Institute of Transportation Studies (ITS) at the University of California, has been conducting a cohort survey of electric vehicle purchasers in California every year over the last four years (2015-2018). For the purposes of this study, we include phases 1–3 of the survey effort:

- Phase 1–1.5: Purchasers of EVs from 2010 to 2015
- Phase 2–2.5: Purchasers of EVs from 2015 to 2016
- Phase 3: Purchasers of EVs from 2016 to 2017

The respondents to the survey were selected from the California Clean Vehicle Rebate Project (CVRP), a rebate program for purchasers and lessees of EVs within California. The CVRP is administered by the Center for Sustainable Energy, which has an agreement with the University of California to provide contact information for rebate applicants for recruitment to participate in the survey. Altogether, phases 1–3 include 15,275 respondents, all of whom applied for the CVRP rebate following the purchase or lease of a PEV.

The survey itself supports many projects investigating a broad array of topics at the PHEV Center, including consumer purchase behavior and attitudes, driving behavior, and charging behavior. For the purposes of this project, we used data from the survey responses to understand the frequency of charging broken down by technology type (short-range/long-range BEVs and PHEVs). Since there were very few BEV with approximately 200 mile range in the survey data (Chevrolet Bolts had just been released), we grouped the BEV 200 and 300 technologies into the same charging frequency distributions.

A single technology type corresponds to each respondent. The probability that a given vehicle at a given charging rate decides to charge on a given day is also constructed entirely from the CVRP survey data. We observe each respondents' charging behavior over the course of a week, specifically how many times they charge their vehicle at each charging level (also given the PEV model they are driving). The number of charging events for each respondent can then be used to
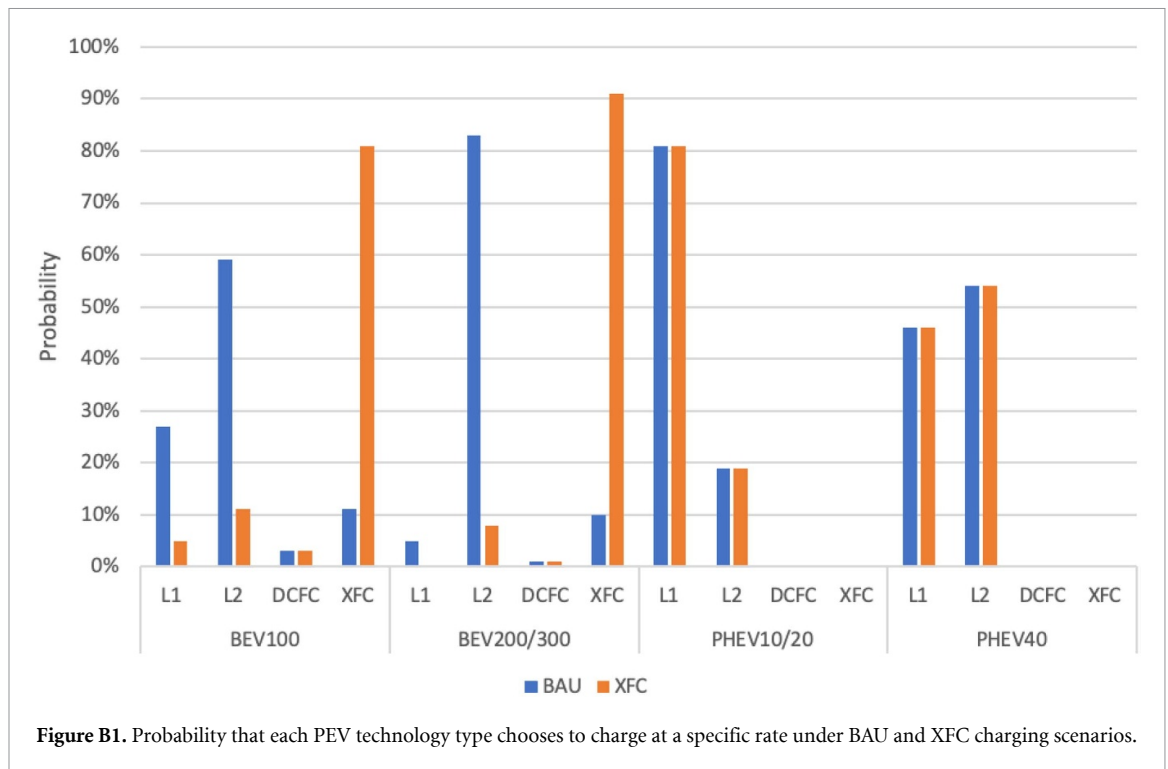
Figure B1. Probability that each PEV technology type chooses to charge at a specific rate under BAU and XFC charging scenarios.

calculate the probability that they charge on a given day.

For each charging event, we simulate the rate that each individual vehicle charges from a set of distributions on charging rate that depends on the technology type of the vehicle (short range vs. long range and PHEVs vs. BEVs). The charging rates under the BAU charging scenario are also constructed from the PH&EV Center cohort survey data. Each respondent was asked a series of questions regarding their vehicle charging behavior, including where, how often, and how fast they charged their vehicle. We summed the responses for speed of charging rate by technology type. The total number of charging events from the respondents corresponding to each technology are as follows:

- Short-range PHEV (10–20 miles): 1,053
- Long-range PHEV (40–50 miles): 9,005
- Short-range BEV (100–150 miles): 6,088
- Long-range BEV (200+ miles): 5,734

Under the BAU charging scenario, we assume that all BEVs purchases after 2021 are XFC capable, but it is assumed that nighttime charging behavior via Level 1 and 2 rates are still the dominant behavior (see table 8). Also, whereas XFC events are not observed in the CVRP survey data because XFC is not yet available, it is assumed that DCFC charges (at 50 kW) from vehicles after 2020 all switch to XFC (i.e. only older BEVs that are not XFC capable continue using DCFC). Under the XFC scenarios, the probability of charging by charge level shifts due to our assumption that all vehicles in the stock in 2030 that are XFC

capable will choose XFC every time. Therefore, only vehicles that are not XFC capable charge at L1, L2, and DCFC under the XFC scenarios.

Charging time distributions by charging speed are constant across the BAU and XFC scenarios. What varies is how charging speed events are distributed across vehicle types between the BAU or XFC scenarios. After 2020, we assume all new BEVs choose to exclusively charge using XFC infrastructure.

There are approximately 9.2 million charging events from ChargePoint. However, this dataset represents only one network of public charge usage and does not consider home-charging events, which may skew the distributions to different times of the day (note that approximately 80%-85% of charging takes place at home). The EV Project from Idaho National Labs provides a fairly comprehensive sample of charging behavior separated into categories of charging rate (L2 and DCFC, no L1 charging), location (home and public), and day of the week (weekday and weekend). Note that the EV Project represents charging behavior of an older generation of electric vehicles (spanning 2011 through 2013) and may not be representative of current day PEV owners. Geographically, the data span 17 locations across the United States (Washington, Oregon, San Francisco, Los Angeles, San Diego, Phoenix, Tucson, Dallas, Houston, Chicago, Nashville, Memphis, Chattanooga, Atlanta, Knoxville, Philadelphia, and Washington, DC). The residential charging load may provide a better sample of home-charging behavior and perhaps it would be possible to hypothesize that the charging behavior of L1 chargers may be relatively similar as these distributions represent the charge start time rather

than the overall duration. Therefore, we assume that the start time of the charging distributions for L1 and L2 are the same for home-charging events. The L2 public-charging profiles are substantially smaller in size than the public infrastructure data from ChargePoint.

The two datasets are combined with 85% of charging conducted at home versus at public stations. The final distributions are therefore weighted to reflect this assumption. Data from the Idaho National Lab (INL) project are provided in 15-minute increments while the simulation operates in 10-minute increments and therefore some interpolation is required to match the time intervals. We combined the resulting data with the EVGo DCFC charge time distribution to create the full set of charge time distributions needed for the simulation. Under the XFC scenario, all vehicles that are XFC capable choose XFC for all of their charging events. The time of day that charging starts for XFC is assumed to be the same as for DCFC.

Appendix C. XFC mitigation scenarios

The procedure assumes that the charging behavior of future electric vehicles will be the same as current charging patterns. However, in the XFC scenarios, we assume that electric vehicle owners will shift their charging patterns away from L1 and L2 and instead charge predominantly on XFC if their vehicle is XFC capable. The start time of XFC events are assumed to mirror that of DCFC events.

In light of the extreme power requirements from XFC (which we assume to be at a minimum 350 kW), the charging infrastructure will have different implications for the electricity grid infrastructure than other PEV charging infrastructure. We think it is reasonable to assume that XFC station operators would want to mitigate spiky demand associated with instantaneous high-power demand that are relatively rare compared to electric vehicles (Qin *et al* 2016, He *et al* 2019, Rajagopalan *et al* 2013, Muratori *et al* 2019, Zhang *et al* 2015, Muratori *et al* 2019). Under current rate structures, many station operators may face high demand charges for XFC-like demand, which may strain the profitability of such a charging station (Burnham *et al* 2017). Our mitigation scenarios employ the use of storage to reduce the charging demand below certain cutoff values while charging the batteries at the optimal time based on real-time electricity rates. The deployment of storage is an exogenous input because they operate at a level below the bulk power system in order to mitigate demand charges (which is a distribution infrastructure issue). The mitigation scenarios are an attempt at simulating the behavior of charging station owners but may not accurately reflect optimal economic decisions for initial installation of storage.

Peak shifting The peak shifting scenario is intended to reflect the installation of an unconstrained amount of storage at XFC stations that are employed such that the charging demand does not exceed a predefined threshold and the load that would exceed this peak would then be shifted to off-peak hours. The peak demand is a dynamic value that changes every day, in each region, and is defined as 5% above the mean of the total daily charging demand. With this cutoff selection, approximately 7%-8% of the demand occurs above the cutoff. Again, this is not to be confused with the electricity grid peak, which may occur at entirely different times. Charging load above the peak is exogenously subtracted from the total charging demand and added back into the GOOD model as a decision variable so that the system can endogenously determine what time the load would be shifted to (either backward or forward in the day, with a daily constraint that prevents the reallocation of the load from exceeding the peak value in any given day).
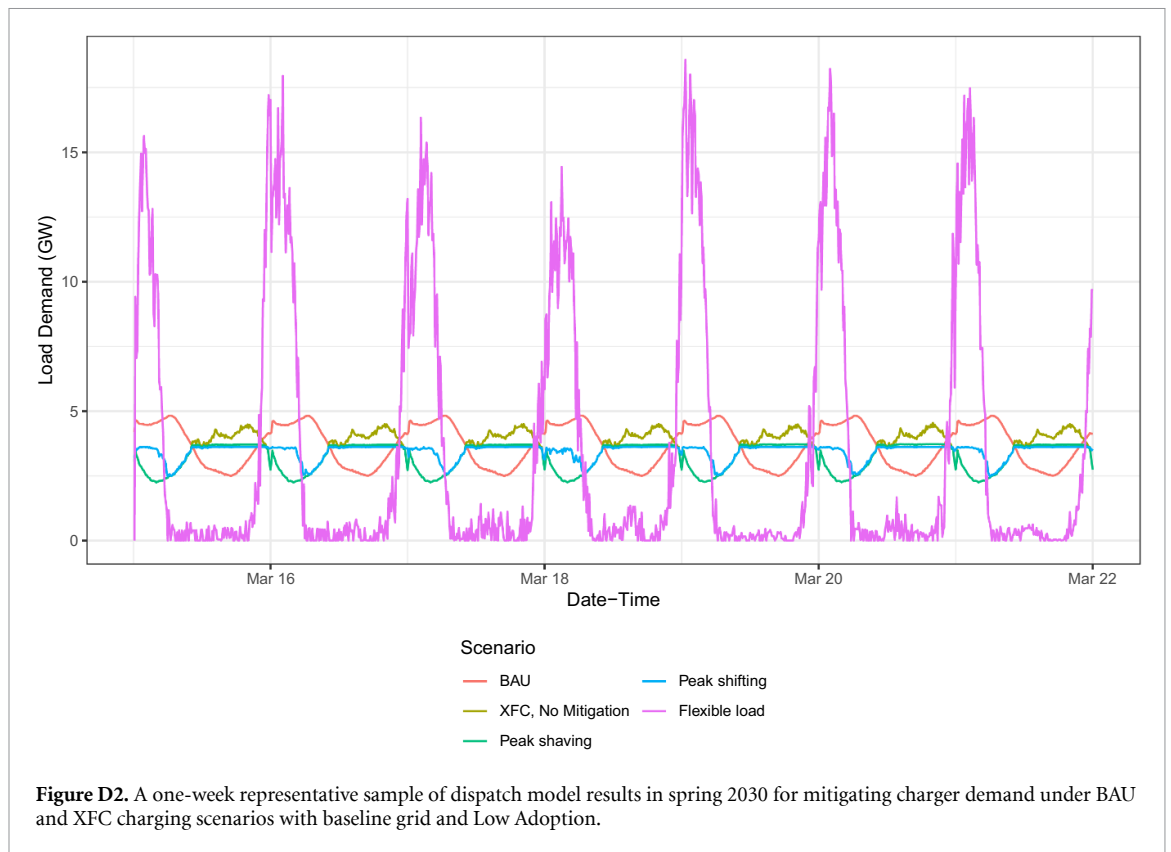
Peak shaving Peak shaving is similar to the peak shifting scenario except that it assumes that station managers also couple the storage units with on-site renewables that charge the batteries. This entirely removes the peak charging demand from the GOOD model, and the load exceeding the peak is assumed to be met entirely with renewable generation. The peak shaving scenario is meant to capture station operator behavior that attempts to operationally avoid demand charges by removing peak charging loads from the grid. In this scenario, we remove charging load above the peak exogenously, but we do not add it back as a decision variable as in the peak shifting scenario.

Fully flexible load Lastly, the fully flexible load assumes that XFC station operators have an excess capacity of storage and manage the entirety of the XFC demand load through flexible storage units. This then allows our system operator to endogenously determine when the storage load is charged over a 1-day period by the grid.

Appendix D. Vehicle charging behavior

Our modeling begins with a simulation of vehicle load demand from charging under two different conditions. The first of which is a BAU scenario where future PEV owners are assumed to charge in a similar manner to current time of day charging behavior. The second is XFC, where charging time shifts to charging like current day DCFC distributions.

In figure D2, we observe how charging loads differ from the BAU charging demand (red) and the baseline XFC charging demand with no mitigation (gold line). The peak shifting (blue line) was designed to reflect the removal of the peak load via local battery storage, which would allow the station operator to determine when to fulfill the charging demand such that the peak load is not exceeded in a given day. This primarily shifts the load to early morning

Figure D2. A one-week representative sample of dispatch model results in spring 2030 for mitigating charger demand under BAU and XFC charging scenarios with baseline grid and Low Adoption.
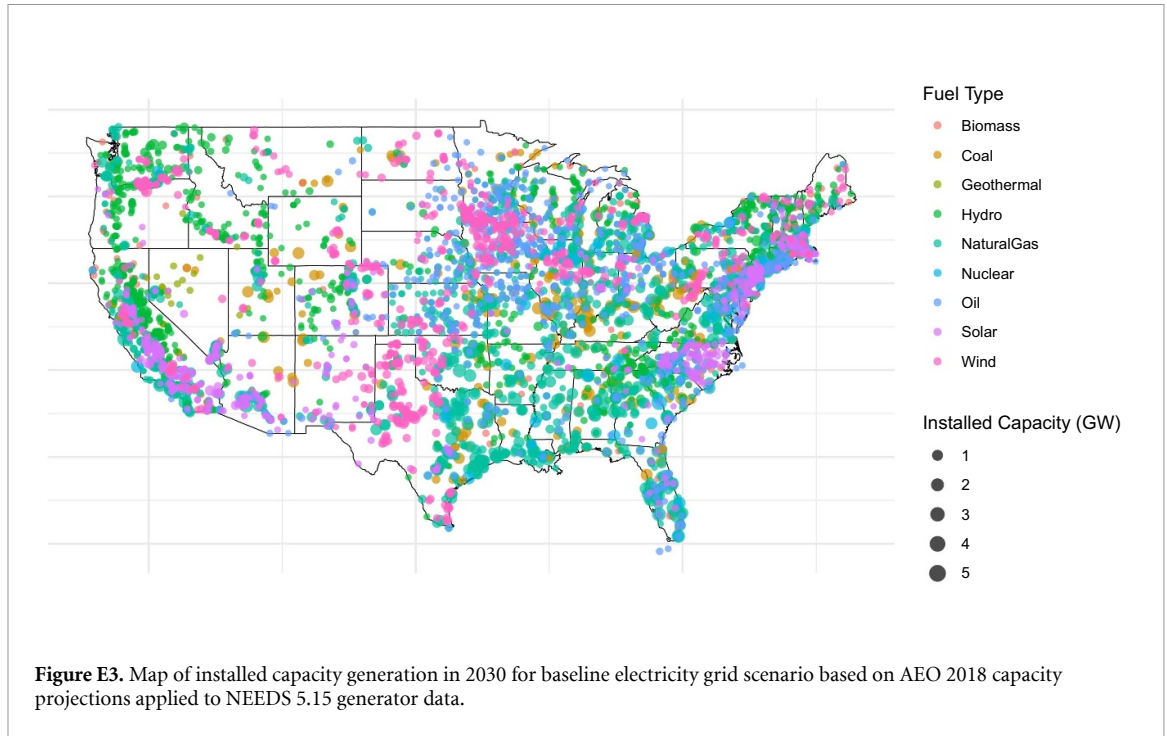
hours, though this may vary from region to region. The peak shaving scenario (green line) is identical to the shift except peak load is removed rather than redistributed to later times. Lastly, we also ran a scenario that allows for all of the charging demand load for XFCs to be entirely flexible with an excess of local storage. In the flexible load mitigation scenario (purple line), we find that the vast majority of charging happens in the evening hours with a peak in the early morning, though there is a non-negligible amount of charging that still occurs throughout the day. This decision-making process is guided by the GOOD model's minimization of cost, thereby causing storage to charge at lowest cost times. It should be noted that the aggregate load demand from the variation can vary by a fairly large amount (as much as 10%)—this explains the discrepancy between the BAU and XFC load demand scenarios, and in turn driving some of the difference in quantity of emissions.

Our modeling of station mitigation of XFC is meant to provide some context into strategies that may align station operators with costs and constraints of the electricity grid. While there are no empirical data on mitigation measures for XFC technology (because XFC is not widely deployed yet), these scenarios provide some insight into how charging patterns could change if station operators deploy on-site renewables and/or battery storage. We calculate the required storage capacity nationwide required to allow for the observed charging profiles in the XFC mitigation scenarios. Under low adoption of

EVs, both peak shaving and shifting scenarios require about 30 GWh of storage while the fully flexible load scenario requires about 360 GWh. Under high adoption of EVs, both peak shaving and shifting scenarios require about 195 GWh of storage capacity while the fully flexible load scenario requires about 1,660 GWh of capacity. Although our attempt to simulate on-site mitigation measures are not based on real-world observations, our bookend results show the relative quantity of XFC load can lead to significant amounts of flexibility in the system. A 15 GW demand represents a substantial amount of load on the grid (the National Renewable Energy Laboratory baseline scenario from the Regional Energy Deployment System Model [ReEDS] projects 30 GW of storage at the wholesale level by 2030).

Appendix E. GOOD model

The constraints describe operational aspects of the economic dispatch, including generation limits based on capacities of the generators, transmission constraints for how much power can be transferred across transmission lines, and ramping constraints for how quickly generators can ramp up and down. The constraints also include requirements for the grid to provide load to fulfill demand. Note that there are separate constraints for scenarios with and without flexible electric vehicle load. The optimization model is run individually across the entire year in 10 minute intervals, separately for each year in the analysis. The equations shown below represent the

Figure E3. Map of installed capacity generation in 2030 for baseline electricity grid scenario based on AEO 2018 capacity projections applied to NEEDS 5.15 generator data.

constraints of the optimization system of the GOOD model.

Demand for electricity must equal load: The baseload demand for electricity (c^{load}) plus electricity demand for charging ($c^{evSubHourlyLoad}$) must equal the total generation and the sum of exports and imports of electricity taking into account transmission efficiency ($c^{trans.loss}$).

$$\sum_{g\in\gamma} x_{gt}^{gen} + \sum_o x_{otr}^{trans} c^{trans.loss} - \sum_p x_{rtp}^{trans}$$
$$- \left(c_{rt}^{load} + c_{rt}^{evSubHourlyLoad} \right) \geq 0, \forall tr$$

Demand for electricity must equal load, with flexible load: Same as the previous constraint except some portion of the charging demand is flexible ($x^{evFlexibleLoad}$) and endogenously determined by the optimization. This constraint is applied to XFC mitigation scenarios containing flexible load.

$$\sum_{g\in\gamma} x_{gt}^{gen} + \sum_o x_{otr}^{trans} c^{trans.loss} - \sum_p x_{rtp}^{trans}$$
$$\times \left(c_{rt}^{load} + c_{rt}^{evSubHourlyLoad} + x_{rt}^{evFlexibleLoad} \right) \geq 0, \forall tr$$

Generation cannot exceed available renewable resources: Generation of renewable electricity cannot exceed the resource supply ($c^{max.renew}$) of each of the renewable resources (γ).

$$c_{rt}^{max.renew} - \sum_{w\in\gamma} x_{wt}^{gen} \geq 0, \forall rt$$

Capacity constraints: Each generator may not generate power in excess of their corresponding

generation limit ($c^{max.gen}$) nor may they generate power less than 0.

$$c_g^{max.gen} - x_{gt}^{gen} \geq 0 \text{ and } x_{gt}^{gen} \geq 0; \forall gt$$

Transmission flow constraints: Transmission of power cannot exceed a transmission line's capacity between any two regions ($c^{max.trans}$).

$$c_{ro}^{max.trans} - x_{rto}^{trans} \geq 0 \text{ and } x_{rto}^{trans} \geq 0; \forall rto$$

Ramping constraints: The generation difference between one time period and the next cannot exceed the ramp rate (c^{ramp}) of each generator.

$$c_g^{max.gen} c_g^{ramp} + x_{g,t-1}^{gen} - x_{gt}^{gen} \geq 0; \forall gt$$

$$x_{gt}^{gen} - x_{g,t-1}^{gen} + c_g^{max.gen} c_g^{ramp} \geq 0; \forall gt$$

Flexible load balancing constraint: The flexible electric vehicle load ($x^{evFlexibleLoad}$) cannot exceed the total electric vehicle daily load ($c^{evDailyLoad}$).

$$\sum_{t\in\chi} x_{rt}^{evFlexibleLoad} - c_{rd}^{evDailyLoad}; \forall rd$$

PEV load threshold constraint: This constraint prevents the total electric vehicle load (sum of static sub-hourly load and flexible load) from exceeding a predetermined daily threshold value ($c^{hourlyCutoff}$).

$$x_{rt}^{evFlexibleLoad} + c_{rt}^{evSubHourlyLoad} - c_{rt}^{hourlyCutoff} \leq 0; \forall rt$$

The generator inputs for the GOOD model include all generators in the United States in 2030. The data account for existing generator assets in 2018, in addition to retirements and new installed capacity by 2030 according to the AEO 2018 projections for capacity. Figure E3 provides a graphical overview of the generators in the United States broken down by location, size, and fuel type. Our analysis includes two scenarios: a baseline grid and a high renewables scenario that increases the installed renewable capacity of wind and solar in the United States by 300%, which acts as a bookend for how a system with relatively high levels of renewables can affect emissions from charging events.

The GOOD model used to simulate the U.S. electricity grid makes specific tradeoffs in order to operate at the resolution required for this analysis. The model does not contain start-up or shut-down constraints to avoid turning the dispatch model into an integer program. This may lead to a slight bias towards generators with long start-up times but allows for a larger scale of analysis. The regional basis spans the entire continental U.S., which would be computationally impossible with a mixed integer program. Additionally, the model is not a capacity expansion model, instead taking exogenous growth in generator capacity and installations from U.S. Energy Information Administration projections. It is possible that incorporating capacity expansion as an endogenous process would lead to a different generator composition in the future.

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