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Evaluating future emissions from electric vehicles across the United States with a changing electric grid mix under the Clean Power Plan

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Summary

In the United States, the transportation sector consumes approximately five billion barrels of oil annually and accounts for nearly a third of greenhouse gas emissions. The potential climate impacts of the transportation sector has led to a transition towards cleaner, alternative fuel vehicles such as electric vehicles (EVs)—touted as "zero-emission" vehicles. The transition has been accelerated by policy such as the Zero Emissions Vehicle (ZEV) mandate in California and incentives such as the federal Plug-In Electric Vehicle Credit (IRC 30D). However, if the ultimate goal of the transition is to create a cleaner transportation system, a proper accounting of emissions is necessary to understand the true impact of EVs. We construct a nationwide electricity dispatch model based on outputs from the Environmental Protection Agency's (EPA) Integrated Planning Model (IPM) used in the assessment of the Clean Power Plan (CPP). Using future projections of EV sales as well as a number of scenarios for charging behavior, a profile of electric vehicle emissions can be captured on sub-state level and importantly across a lengthy time span from 2016 through 2050. The time periods being captured are significant due to the lack of existing literature on EV emissions as the electric grid changes and cleaner sources of electric capacity are developed. We are able to demonstrate large regional differences in emissions with gradual improvement in emissions as the electric grid becomes cleaner over time. Consequential emissions of EVs can result in up to 50 million tons of CO_2 annually by 2030 depending on the scenario of electric grids, but we find that the implementation of CPP produces far greater impacts and can result in changes in total grid emissions of 500 million tons of CO_2.

Keywords: BEV, ZEV, regulation, LCA, emissions

1 Introduction

In 2008, the first commercial electric vehicle (EV), the Tesla Roadster, became available on the United States market followed shortly by the Nissan Leaf and Chevrolet Volt in 2010. There are currently over 30 models of fully electric battery electric vehicles (BEVs) and plug-in hybrids (PHEVs) on the US market today. Electric vehicles have also been heavily promoted by a variety of policies, both from a supply side (Zero Emission Vehicle (ZEV) mandate and incentives within the Corporate Average Fuel Economy (CAFE) standards) as well as from the consumer side (vehicle purchasing credits, carpool lane access, etc.). The ultimate goal of shifting away from conventional internal combustion engine vehicles and adopting electric vehicles is to decarbonize the transportation sector, a necessity to meet goals such as AB32 (reduction of all greenhouse gas emissions by 80% below 1990 levels by 2050 in California) and to an extent to meet the current and future Greenhouse Gas Emission Standards set by the Environmental Protection Agency (EPA).

How do electric vehicles fare in the context of greenhouse gas emissions? While EVs are often considered to be ZEVs, in reality the charging of the EV batteries may produce upstream emissions as a result of producing the electricity necessary to drive the vehicle. Our work aims to investigate these emissions in an extraordinarily detailed manner by modeling the entire United States electricity grid and associated changes over future events as adoption of electric vehicles continues to grow out until 2040. We measure the consequential emissions, that is the emissions attributable to a changing population of electric vehicles rather than average emissions, or the emissions resulting from the average emissions of the entire grid.

1.1 Literature review

Our modeling work consists of several components and therefore draws upon several bodies of literature. In order to estimate emissions from electric vehicles, we first simulate vehicle charging behavior to determine when drivers of EVs are impacting the grid and to what extent. For this section, we reference several EV charging studies. A much broader set of literature is examined to compare and contrast measurement of EV emissions as well as the methods that different studies have employed. Lastly, since our analysis extends far into the future, much of the change in the electric grid is determined by policies such as the Clean Power Plan (CPP), which is described in greater detail below.

1.1.1 Electric vehicle charging studies

Vehicle emissions can be highly dependent on the time of charging due to the fact that different generators will be responsible for the marginal emissions associated with EV charging at different hours of the day. We review several studies that examine vehicle-charging behavior to inform the vehicle simulation model. Several studies have examined economic operation of electric vehicle charging in other countries such as Germany (1) or Japan (2) with an in-depth look at how charging and routing behavior are related. In particular, Sun's paper examines preferences based on speed of charging and price of charging, both important determinants for behavior. Another important aspect of charging is wait times related to vehicle arrivals at charging stations, a topic examined by Carvalho et al. to understand topics of fairness in charging (3). Perhaps most relevant to our work is utility controlled charging which allows utilities to optimize charging behavior to be in line with some of their electricity grid constraints. Bailey and Axsen provide a case study of this topic for new EV car buyers in Canada and find support for this charging scheme among half to two-thirds of the respondents (4).

1.1.2 Electric vehicle emissions studies

Emissions from electric vehicles, both from battery production and upstream emissions associated with electricity production, are a well studied topic spanning well before even EVs were commercialized on the vehicle market. Our review focuses on the upstream emissions, as this is the relevant quantity for our work. One of the first studies in this area was a process-relational life cycle analysis (LCA) model conducted in 2000 by Japanese researchers comparing the CO_2 emissions of EVs to gasoline vehicles (5). While average electricity emissions factors were used for the charging of the vehicle, this study laid the groundwork for determinants of EV emissions for future work. As studies of electric vehicle emissions were developed, important details were determined to be critical to accurately attributing emissions to the new transportation technology such as electricity supply of the power sector (6), or the demand of marginal fuels and timing of charging (7). Soon afterwards, Weber et al. pointed out that the limits of knowledge of grid electricity and associated emissions in the field of LCA can lead to important differences between estimates of true emissions factors for CO_2, SO_2, and NO_x (8). In Michalek et al., this issue is circumvented by including a full sensitivity range on different emission rates from coal and natural gas plants (9) or by creating scenario based grids that are cleaner on average (10). However, many studies at this point began investigating the concept of average grid emissions versus marginal grid emissions, an important concept for proper attribution of EV impacts. An early case study of this concept first emerged in Ma et al. as part of a larger LCA study of conventional vehicles versus BEVs in California and the UK (11). While some important studies still examine emissions based on average grid emissions (12), the marginal grid mix studies grew significantly in detail to incorporate various critical aspects such as time of day of charging, regional variability, and even pricing (13,14,15). Even as marginal emissions studies grew in quantity and scope, an alternative approach to identify the consequential emissions was introduced by modeling the electric grid. In a series of studies, Weis et al. demonstrated the capability to measure emissions with extremely high resolution by modeling a hypothetical electric grid with high renewable penetration (16) and as a case study in the PJM interconnection grid (17,18). Our work is most similar to Weis et al. in measuring consequential emissions, but we construct a grid for the entire country and across a significantly longer time span. Investigation of deep future grid impacts on EV emissions has been sparsely explored, the only current study examining this topic is a case study in Germany in 2030 (19). The literature covered on this topic is not comprehensive as there are several hundred research papers on the topic of EV emissions but the review provides important historical context on the trajectory of research in this area. Our work is at the forefront of exploring consequential EV emissions and provides an unprecedented level of detail on integrating electric vehicles and the electric grid both spatially and temporally.

1.1.3 Clean Power Plan studies

In 2013, President Barack Obama announced a plan to reduce carbon dioxide emissions from electric generation sources. The ultimate result was EPA's Clean Power Plan, a rule that essentially reduces allowable CO_2 emissions from fossil fuel generators in the electric sector. The impacts of the plan have been studied in great detail with perspectives on efficiency of power plants (20) and shifts in fuels in response to the regulation (21). Of particular interest to the mechanism of compliance in our electric grid model is cooperation (or aggregation) of the regulation across multiple states, the benefits of which are documented in a study by Oates and Jaramillo (22). Our work draws directly from data used in the Regulatory Impact Assessment of the CPP as the hypothetical future grid infrastructure, which is described in greater detail in Section 2.4. The Clean Power Plan implementation is currently awaiting evaluation by the Supreme Court and has been staunchly opposed by the current Trump administration. However, while there is a great deal of uncertainty as to whether or not the CPP regulation will be enacted, we model the grid both with and without the CPP regulation as a demonstration of the importance of its effects on EV emissions.

While much work exists in the area electric vehicle emissions, it is novel for several reasons. The scope of our work covers the entire US, we construct a model of the electric grid that includes trading between regions, an aspect that is missing from the current literature. While works that include marginal emission factors are suitable for small numbers of electric vehicles, at larger volumes that requires moving up the generator dispatch curve, a model of generator operation is necessary to accurately capture the emissions associated with the grid. Perhaps most significantly, this study examines electric vehicles and the electric grid into the future, allowing for integration of changes in the grid with the rising uptake of EV technology.

The remainder of the paper is organized as follows: Section 2 describes the components of the model and the data associated with inputs required for the model's operation; Section 3 contains our primary results broken into three components: vehicle simulation results, grid dispatch outcomes, and final emission measurements; lastly we conclude with a discussion of the significance and implications of our work in Section 0.

2 Data and Methods

2.1 Vehicle simulation model

We develop a vehicle simulation model in order to estimate the additional electric load resulting from the charging of electric vehicles. The simulation is run over the years 2016, 2018, 2020, 2025, 2030, and 2040, hourly over the entire year. The requisite data to determine EV load includes: the number of EVs on the road disaggregated into their respective balancing regions, their daily travel behavior and associated charging requirements, time of day of vehicle charging, and the rate of charging.

The EV charging simulation draws daily trips for each EV on the road from the 2009 National Household Transportation Survey (NHTS). The NHTS contains detailed trip information including daily trip distances and arrival times at home and at work (if applicable). We examine two scenarios of charging: convenience charging which is when drivers charge as soon as they arrive at home, and delayed charging which is when the charging of the vehicle is delayed several hours after the driver arrives at home. For PHEVs, the daily trip distance is assumed to be only be up to their maximum range for a single day (the rest of the distance is traveled on gasoline) while for BEVs, the daily trip distance is capped at their maximum respective ranges with the exception of the fast charging where all daily trip distances are allowed to be drawn. For both scenarios of charging, the vehicles are assumed to charge at a standard Level 2 charge of 6.6 kW. To simulate the total EV load ($c^{\text{EV.load}}$) in a specific time period (hourly) t and for a region r, we draw from the NHTS data for driving distance ($c(x)^{\text{driv.dist}}$) on day d and calculate the respective number of hours needed to charge the vehicle given the travel demand using a Level 2 6.6 kW charger. The load is then distributed across a certain index of hours based on corresponding draws to the home arrival time ($A(x)$) as seen in Equation (1).

$$c_{tr}^{\text{EV.load}} = \sum_i c(x)_{idr}^{\text{driv.dist}} \bullet c_i^{\text{veh.eff}} \Big/ 6.6\text{kW} \sim A(x)_{it} \tag{1}$$

Once the EV charging demand ($c^{\text{EV.load}}$) is simulated, it is then combined with the baseload electricity demand for all other services as an exogenous input into the grid dispatch model.

2.2 Vehicle projection data

Projections of EV sales are drawn from literature representing lower bound and upper bound estimates of technology adoption. The lower bound scenario is represented by the Energy Information Agency's Annual Energy Outlook 2016 projections which estimates a stock of slightly lower than 7 million EVs on the road in 2040 while the upper bound scenario is represented by a National Academy of Sciences study which estimates a stock of approximately 75 million EVs on the road in 2040 (see Figure 1). Each of the projections includes a breakdown of EV technologies into PHEVs with 10 and 40-mile ranges and BEVs with 100 and 200-mile ranges. The respective regional and national levels of sales are then allocated into the IPM regions of the dispatch model on the basis of population.

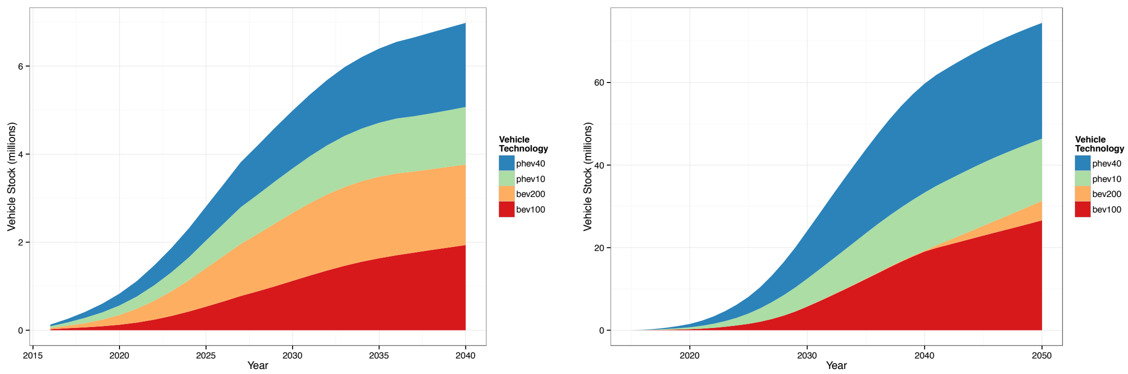

Figure 1: Two scenarios of electric vehicle adoption broken down by vehicle range and type. The EIA projection (*left*) estimates a total stock of approximately 7 million EVs on the road by 2040 while the National Academies study (*right*) estimates a total stock of approximately 75 million EVs on the road by 2040. These estimates represent lower and upper bounds respectively of EV adoption in the US.

2.3 Economic dispatch model

An economic dispatch model is a method of simulating the operation of electric power producing generator units such that it fulfills some demand of electricity at minimum cost to the system operator. The dispatch is defined as a linear optimization system that operates with respect to 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 $c^{\text{gen.cost}}$ and $c^{\text{trans.cost}}$ respectively and the objective function defining the dispatch model is shown in Equation (2).

$$\min_{wrt\; x_{gt}^{\text{gen}}, x_{rto}^{\text{trans}}} \sum_{gt} x_{gt}^{\text{gen}} c_{g}^{\text{gen.cost}} + \sum_{rto} x_{rto}^{\text{trans}} c_{ro}^{\text{trans.cost}} \tag{2}$$

In addition to the objective function of the linear system, there are a number of constraints that comprise the dispatch model, which can be found in Table 1. The optimization model is run individually across all 8,760 hours of each year, separately for each year in the analysis.

Table 1: Economic dispatch optimization model constraints

Constraint	Description
$\sum_{g\in\gamma}\left(x_{gt}^{\text{gen}} + \sum_{o} x_{otr}^{\text{trans}} c^{\text{trans.loss}} - \sum_{p} x_{rtp}^{\text{trans}} - c_{rt}^{\text{load}} \right) \geq 0, \forall tr$	**Demand for electricity must equal load** – The total demand for electricity (c^{load}) must equal the total generation and the sum of exports and imports of electricity taking into account transmission efficiency ($c^{\text{trans.loss}}$).
$c_{rt}^{\text{max.renew}} - \sum_{w\in\gamma} x_{wt}^{\text{gen}} \geq 0, \forall rt$	**Generation cannot exceed available renewable resources** – Generation of renewable electricity cannot exceed the resource supply ($c^{\text{max.renew}}$) of each of the renewable resources (γ).
$c_{g}^{\text{max.gen}} - x_{gt}^{\text{gen}} \geq 0 \text{ and } x_{gt}^{\text{gen}} \geq 0; \forall gt$	**Capacity constraints** – Each generator may not generate power in excess of their corresponding generation limit ($c^{\text{max.gen}}$) nor may they generate power less than 0.
$c_{ro}^{\text{max.trans}} - x_{rto}^{\text{trans}} \geq 0 \text{ and } x_{rto}^{\text{trans}} \geq 0; \forall rto$	**Transmission flow constraints** – Transmission of power cannot exceed a transmission line's capacity between any two regions ($c^{\text{max.trans}}$).
$c_{n}^{\text{rate.std}} \sum_{t,g\in v} x_{gt}^{\text{gen}} - \sum_{t,g\in v} x_{gt}^{\text{gen}} c_{g}^{\text{em.rate}} \geq 0; \forall n$	**Clean Power Plan constraint** – The annual emissions rate of all fossil units (v) cannot exceed an amount defined by the EPA ($c^{\text{rate.std}}$) in an aggregate region (n).

2.4 U.S. electric grid data

The data on the US generator are obtained from EPA's National Electric Energy Data System (NEEDS) model v.5.15, which was used in the Regulatory Impact Analysis of the Clean Power Plan in order to evaluate compliance with the regulation. The data provided is comprehensive and provides all key variables necessary to run our economic dispatch model: generator region, fuel type, CO_2 emissions rates, dispatchable capacity, fuel costs, new installed capacity over time, solar, hydro, and wind representative hourly and seasonal profiles, transmission capacities, wheeling costs, and electricity demand load profiles. As small example of the data, we provide an overview of generator capacities in the United States in 2016 in Figure 2.

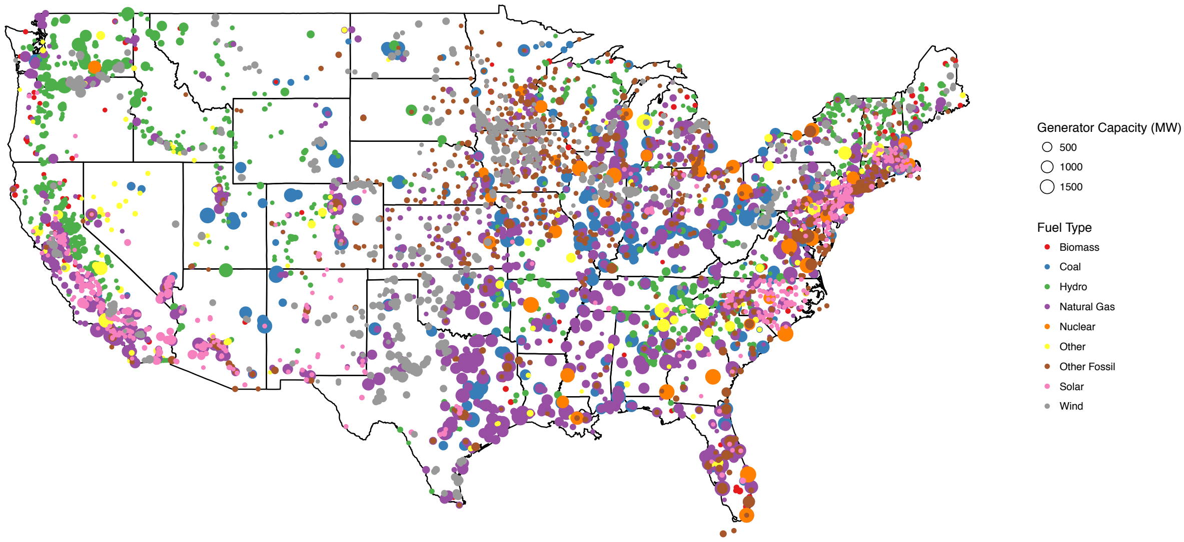

Figure 2: Capacities (MW) of electric grid generators in the United States in 2016 broken down by fuel type

2.5 Overview of scenarios

Our model examines a number of different scenarios in several areas: grid policy (2), no regulation vs. Clean Power Plan implementation; charging scenarios (2), convenience vs. delayed charging; and EV adoption (3), baseline (no EVs), EIA projections, and National Academy projections. These scenarios represent a wide range of potential futures in both the electricity and transportation sectors that allow us to evaluate an array of outcomes and understand the sensitivity of different parameters to affecting these outcomes. In addition, each scenario combination is run across every individual year (2016, 2018, 2020, 2025, 2030, 2040) resulting in a total of 72 optimization runs. Due to the size and magnitude of running an hourly dispatch model over a whole year across the entire country, we leverage the Department of Energy's (DOE) National Energy Research Scientific Computing Center (NERSC) to run the model.

3 Results

3.1 Vehicle simulation results

We simulate electric vehicle load demand on an hourly basis for all electric vehicles adopted over the next three decades. The future load varies quite significantly based on the adoption scenario, in the lower adoption scenario (EIA projections) the load increases from 2 TWh in 2018 (for reference the annual consumption of electricity in the US is approximately 4,000 TWh) up to 35 TWh in 2040. Meanwhile, in the higher EV adoption scenario (National Academies study) the load increases from 2.7 TWh in 2018 up to 280 TWh in 2040. The technology breakdown is slightly different between the projections, particularly as the National Academies projection does not include many 200-mile BEVs until 2030, a short-coming of the slightly older study as a number of commercial 200-mile BEVs are already on the market (e.g. Tesla Model S, Chevrolet Bolt). Nevertheless, the aggregated EV load demand curves are only slightly biased as the number of daily 200-mile trips from the NHTS draws represents less than 1% of the data.

We display a sample of the vehicle simulation results in Figure 3, an example of electric vehicle load over the course of a week in the greater San Diego region in 2030 assuming an adoption scheme of vehicles under the National Academies projection. Figure 3(a) displays the hourly load curves broken down by vehicle technology. The highest demand is actually from PHEV40s while the lower range PHEV10 load demand is about the same as BEV100s, at this point BEV200 load demand is negligible due to the National Academy's assumptions of the 200-mile technology. As the charging scenario represents the "delayed" option, peak load demand occurs between 2-5 AM while the trough in load occurs in the afternoon/early evening. The charge timing is also available in Figure 3(b), which displays the aggregated EV load in combination with baseload demand of electricity. The electric vehicle load is still relatively small in comparison to the total baseline electricity demand, though in some regions the EV demand is a significant portion of the load, particularly in later years of analysis.

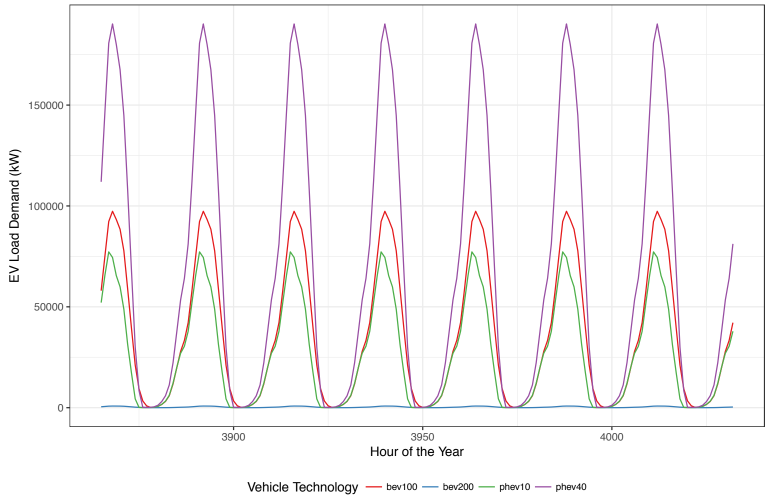

Figure 3 (a): Electric vehicle load simulation results for National Academies Study projection of delayed charging scenario. The load curves represent the aggregate demand of electricity broken down by vehicle technology in 2030 in the greater San Diego region of California.

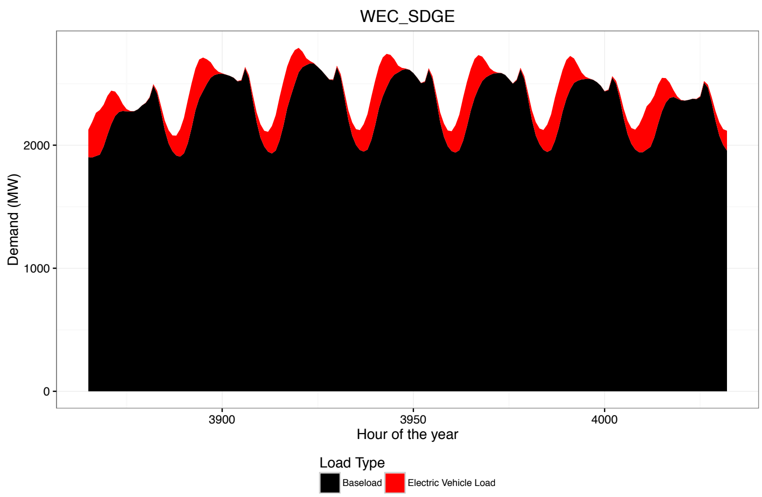

Figure 3 (b): Total electricity demand resulting from baseline demand (black) plus the electric vehicle load demand (red) from the EV load simulation (National Academies Study vehicle adoption projection and delayed charging scenario). The aggregate demand represents load in 2030 in the greater San Diego region of California.

3.2 Dispatch modeling results

The dispatch model results provide direct insight into the operation of all power producing generators for the electricity grid on an hourly basis across the United States. In our analysis, these results include transfer of power between regions (based on existing transmission and future growth of transmission lines). In Figure 4, we display an example of the dispatch model generation results aggregated at the fuel type level for a delayed charging scenario, National Academy's projection of adoption of electric vehicles, and a under cleaner grid due to CPP regulation for the greater San Diego region in 2030. The figure displays only generation in the region and therefore may not match the exact load demand because of transmission: imports and exports of power into the SDG&E region are not directly observed. While Figure 4 displays mainly the uptake of solar power during the day and a flexible baseload of natural gas, the fuel composition of load serving entities may differ quite drastically in other regions. For example, the Pacific Northwest has very high dispatch of hydropower while the Eastern US relies much more on coal and nuclear power.

Nevertheless, there is a clear observable trend of increasing natural gas and renewable dispatched resources across the US as new capacity is installed and CPP regulations become stricter.

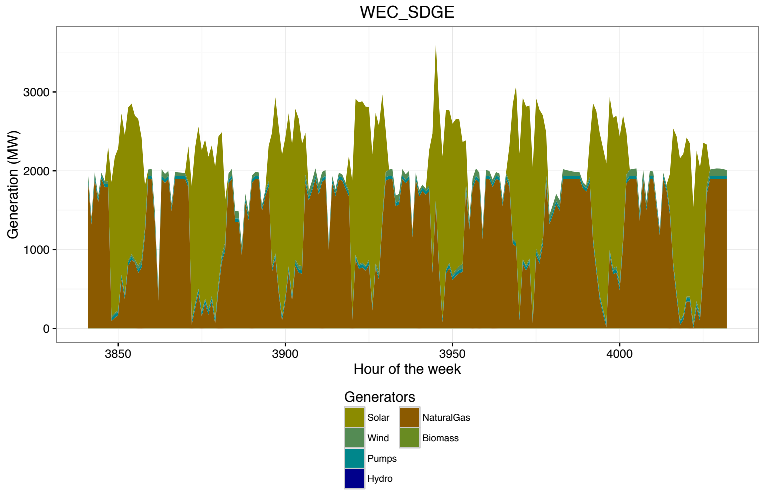

Figure 4: Economic dispatch generation results over a week period in the greater San Diego region in 2030. This particular dispatch represents a scenario with delayed EV charging under National Academy volume projections and a cleaner grid under CPP. During the day, solar generation is primarily balanced by natural gas with the same resource fulfilling baseload generation during the evening.

Figure 5 shows the net consequential impact of electric vehicle charging on generation assets in the SDG&E region in 2030. We calculate the consequential generation by subtracting the baseline generation scenario from a scenario with electric vehicles. The difference between these two scenarios (one with electric vehicles and the identical scenario without EVs) results in generation assets that respond to the load differently as seen in Figure 5. Similarly to aggregate generation, the consequential generation does not necessarily match the demand profile of EV charging because of transmission of power between regions. As a matter of fact, the consequential generation often ends up being negative in certain hours as the optimization of the generation system may lead to lower generation at certain times as imports of energy are used instead.

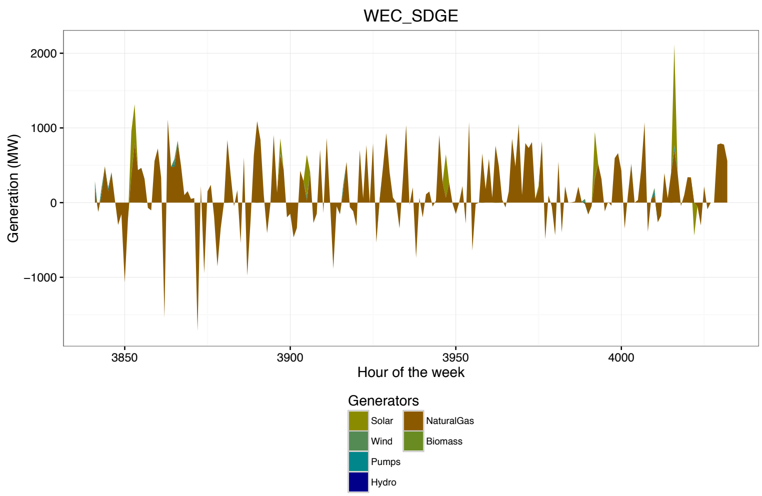

Figure 5: Consequential dispatch of EV load in the greater San Diego region in 2030 (delayed charging, National Academies projection, CPP scenario), the difference in generation dispatch between a scenario with EV adoption and without. Note that the consequential dispatch does not exactly match the EV load due to transmission of power across different regions.

The consequential dispatch ultimately effects the net emissions resulting from the adoption of electric vehicles on the road. Based on these results, we are able to calculate the emissions resulting directly from the charging of EVs all across the United States.

3.3 Emissions from electric vehicles

Based on the consequential dispatch of electricity we are able to estimate the consequential emissions associated with the charging of electric vehicles across the US. The emissions can then be aggregated to regional levels (instead of by generator) across the entire year to represent the "average" consequential emissions of an electric vehicle. These emissions are translated into equivalent emissions rates based on the efficiency of the electric vehicle, as shown in Figure 6. The figure displays spatial results aggregated as an average over the course of the entire year broken down into EPA IPM segments. The maps provide an approximate average consequential emission rate for vehicles charged by power produced from those regions, it may be the case that a vehicle charged in one region is actually receiving power produced from an alternate region.

In Figure 6 we compare the spatial distribution of consequential emissions as a function of several scenario differences: convenience versus delayed charging and EIA (low volume) and National Academies' (high volume) EV adoption projections. The consequential emissions intensity is highly dependent on the region: typically we find that the cleanest areas are on the West Coast, the South, and the Northeast. However, we note the majority of the "worst" consequential emission rates are approximately between 300 and 400 grams of CO_2 per mile, which translates to between 22.2 and 29.6 MPG while in many regions where EVs are currently located the consequential emission rates lay between 0 and 150 grams of CO_2 per mile (59.2 MPG). Since the 2018 time point is close enough to the present, there is not much divergence in adoption and therefore the emissions are quite similar between EIA and National Academy projections. However, there is a definite difference when considering the timing of charging but there isn't a clear trend and the emissions impact is dependent on the region. For example, there is a noticeable improvement in consequential emissions in Montana, Missouri, and Louisiana regions when vehicles use delayed charging rather than convenience charging. On the other hand, the consequential emissions in Texas, Utah, Colorado, and Nebraska worsen when moving from convenience charging to delayed charging.

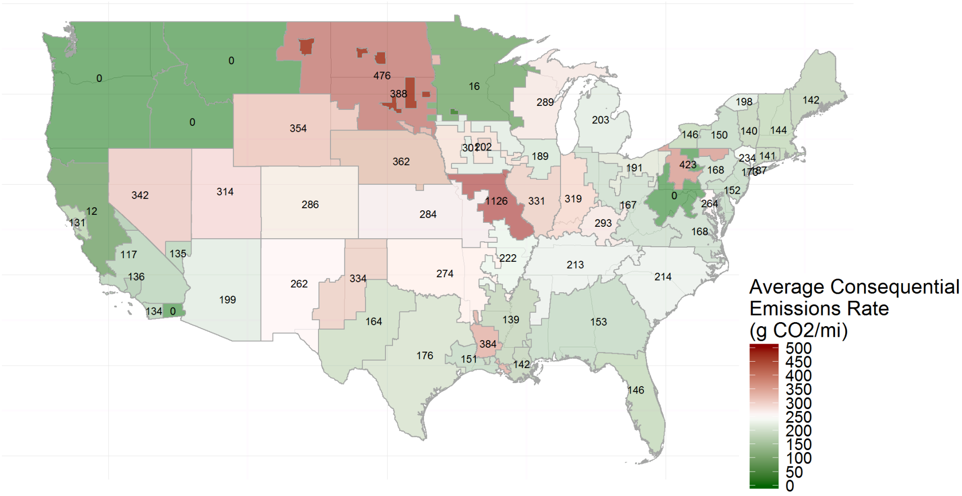

Figure 6: Average consequential electric vehicle emissions by EPA NEEDS v5.15 IPM regions. The emission rates are scaled to gCO_2/mi with white (250 gCO_2/mi) at an equivalent of about 35.5 MPG. Scenario: CPP, convenience charging, EIA

We display the total annual emissions of the entire electricity grid in Figure 7. We notice an immediate difference in terms of total emissions between the "No CPP" and "CPP" scenarios, due to the effect on the entirety of the electric grid. The difference between these two scenarios swamps the differences resulting in the transportation sector from electrification, both adoption and charging scenarios are outweighed. If we focus on the differences between consequential emissions as seen in Figure 7(b), we are able to examine how the total electric vehicle emissions are affected by different levels of adoption of EVs, their respective charging scenarios, and changes to the electric grid. Of course at higher levels of adoption, the emissions from electrified transportation is higher (though overall transportation emissions may be lower due to offsetting of traditional combustion engine vehicle emissions which is outside the scope of this analysis). Interestingly, we find that delayed charging to offset peaking actually increases emissions on average. This is typically due to the fact that coal baseload power is being employed for charging EVs during delayed periods in earlier years and even in CPP when a transition towards lower carbon intensity is made, solar during peak hours still leads to lower emissions in later years.

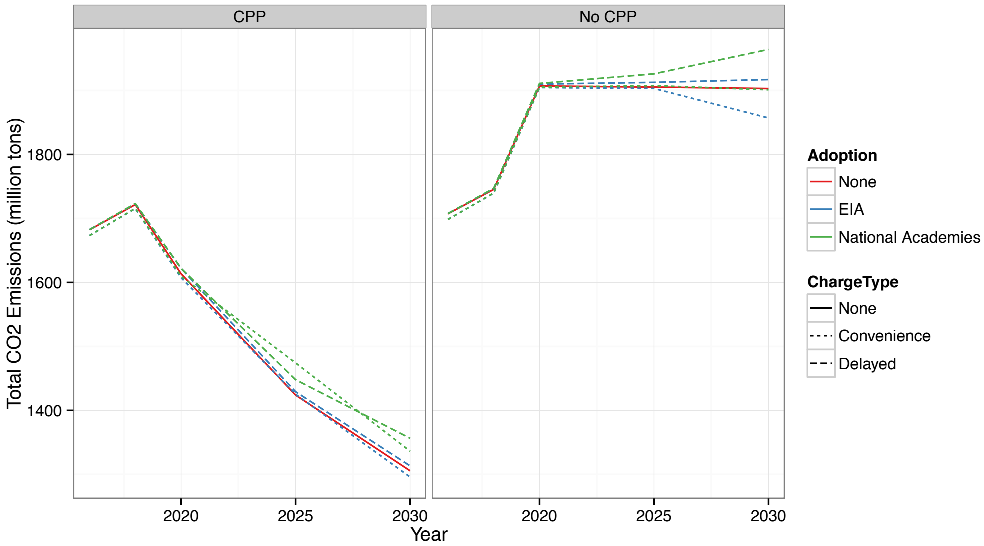

Figure 7(a): Total annual CO_2 emissions from the US grid under different scenarios of electric vehicle adoption, charging behavior, and electric grid policy.

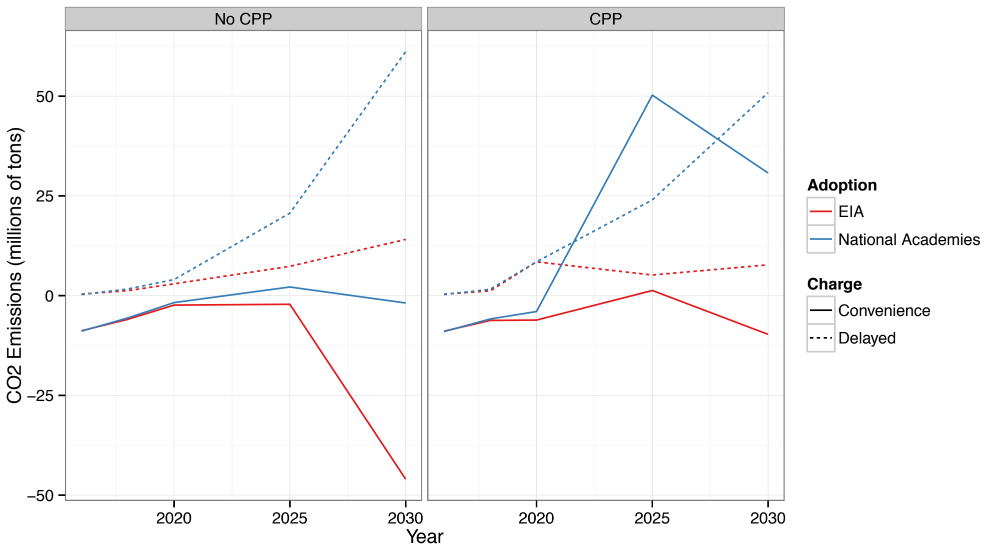

Figure 7(b): Total annual consequential CO_2 emissions from the use of electric vehicles across scenarios of adoption, charging behavior, and electric grid policy.

4 Conclusions and Discussion

Our research provides a novel and detailed investigation into the future of electric vehicle emissions under varying scenarios of electric grid evolution, electric vehicle adoption, and electric vehicle charging patterns. We are the first in the existing literature to examine the consequential emissions of electric vehicles using a national economic dispatch model to simulate the behavior of the electric grid, as well as the first to examine emissions using this method far into the future (on a time-scale through 2030/2040). Depending on the adoption level of EVs and their respective charging patterns, we find an annual total emissions difference of up to 100 million tons of CO_2 annually. One surprising finding is that convenience charging on average actually results in lower consequential emissions than delayed charging, though this outcome differs by region depending on the local generator makeup.

Perhaps our most important finding is the importance of CPP regulation and its respective impact on total CO_2 emissions. In the context of transportation electrification, even the most aggressive adoption scenario of electric vehicles under the best charging outcomes do not approach the decrease in emissions that can be achieved through implementation of the Clean Power Plan (on the order of 50 million tons versus 500 million tons of CO_2). For policy makers, we hope this provides context on the importance of the electric grid in EV emissions and its future evolution can outweigh even a tenfold increase in EV adoption.

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