Environmental Science & Technology

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Emissions and Cost Implications of Controlled Electric Vehicle Charging in the U.S. PJM Interconnection

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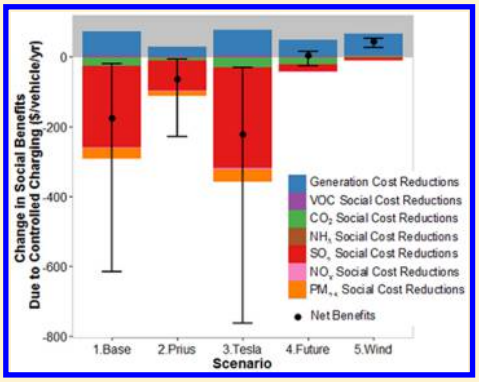
Supporting Information

ABSTRACT: We develop a unit commitment and economic dispatch model to estimate the operation costs and the air emissions externality costs attributable to new electric vehicle electricity demand under controlled vs uncontrolled charging schemes. We focus our analysis on the PJM Interconnection and use scenarios that characterize (1) the most recent power plant fleet for which sufficient data are available, (2) a hypothetical 2018 power plant fleet that reflects upcoming plant retirements, and (3) the 2018 fleet with increased wind capacity. We find that controlled electric vehicle charging can reduce associated generation costs by 23%−34% in part by shifting loads to lower-cost, higher-emitting coal plants. This shift results in increased externality costs of health and environmental damages from increased air pollution. On balance, we find that controlled charging of electric vehicles produces negative net social benefits in the recent PJM grid but could have positive net social benefits in a future grid with sufficient coal retirements and wind penetration.



1. INTRODUCTION

U.S. federal and state policies promote the adoption of electric vehicles as a means to transition to a cleaner transportation system. Passenger vehicles account for 17% of United States greenhouse gas (GHG) emissions[1] and also produce other pollutants harmful to human health and the environment. For example, particulate matter emissions, especially in urban areas, contribute to respiratory illnesses like asthma, pneumonia, and bronchitis.[2] Although electric vehicles have lower tailpipe emissions than gasoline powered vehicles, the changes in emissions associated with vehicle electrification on a life cycle basis will depend on the emissions associated with the operations of the power plants used to charge the battery. Power plants currently produce 71% of national SO_2 emissions, 1% of primary particulate matter emissions, and 14% of NO_X emissions,[4] which cause their own set of health and environmental problems. SO_2 from power plants is a particular concern, as SO_2 is a precursor of particulate matter.[3] Power generation also accounts for over 40% of GHG emissions.[5] Electric vehicle charging may affect these trends. Finally, the additional electricity demand from charging vehicles will affect the operations of the power system and potentially affect the costs of electricity. In this study, we evaluate the economic, environmental, and health costs and benefits of controlled electric vehicle charging in the PJM interconnection. We aim to help inform policymakers and electric power grid operators about the conditions under which encouraging controlled charging will be beneficial for society, as well as to identify which factors are most important for future modeling of the implications of vehicle-to-grid and controlled electric vehicle charging.

Several previous studies have evaluated the emission benefits of controlled vs uncontrolled electric vehicle charging. Table 1 provides a summary of this literature. One of these studies, Choi et. al,[6] examined life cycle emissions, whereas Lund and Kempton,[7] McCarthy and Yang,[8] and Peterson et al.[9] focus only on emissions attributed to charging. None of these studies have included both a detailed model of the power grid with power plant operating constraints and a consideration of social costs of criteria air pollutants and greenhouse gas emissions. We build on previous work and provide new insights about the costs and benefits of vehicle electrification under controlled vs uncontrolled charging schemes. Unlike previous work, we combine detailed modeling of the operating constraints of the electric grid with an estimate of the environmental and health damages from the additional emission due to vehicle charging, in addition to evaluating the change in operating costs. We base our model on the PJM power grid in the Eastern United States (ignoring interregional trade) and include three power grid scenarios for this system to evaluate the near-term effects of controlled charging. The first grid scenario is based on the most

Received: December 1, 2014
Revised: March 26, 2015
Accepted: April 1, 2015
Published: April 1, 2015

DOI: 10.1021/es505822f
Environ. Sci. Technol. 2015, 49, 5813−5819

Table 1. Previous Literature Comparing the Effect of Controlled vs Uncontrolled Plug-in Electric Vehicle Charging on Emissions

author	year	power system	scope	power system model	high wind scenario?	emissions considered	calculation of damages?
Lund and Kempton[7]	2008	Denmark	charging emissions	supply curve with min gen	yes	CO_2	no
McCarthy and Yang[a][8]	2010	California	charging emissions	supply curve	no	CO_2	no
Peterson et al.[9]	2011	PJM and NYISO	charging emissions	supply curve	no	CO_2, SO_2, NO_X	no
Choi et. al[6]	2013	Eastern Interconnect	life cycle emissions	unit commitment and capacity expansion	yes	CO_2	no
this paper		PJM	charging emissions	unit commitment	yes	CO_2, SO_2, $PM_{2.5}$, NH_3, NO_X, VOCs	yes

[a]This work does not explicitly compare controlled and uncontrolled charging, but it does examine the difference in emissions for charging off-peak vs throughout the day.

recent available characteristics of the PJM system; in our second grid scenario, we develop a hypothetical power plant fleet for 2018 that accounts for the retirement of coal power plants; and our third scenario extends the 2018 system to include 20% wind penetration.

2. MATERIALS AND METHODS

Scenarios. We use five different scenarios to investigate how different factors will affect emissions and the costs of charging:

1. Base Case: In this scenario, we assume an electric vehicle fleet based on the $PHEV_{35}$ model in GREET[10] (similar to the Chevy Volt) and a fleet of power plants representing the PJM system in 2010.
2. Small Battery: For this scenario, we modify the base case so that the vehicle fleet is based on the Toyota Plug-in Prius.
3. Large Battery: For this scenario, we modify the base case so that the vehicle fleet is based on the Tesla Model S.
4. Future: For this scenario, we modify the base case to model a power plant fleet in 2018 by accounting for planned new power plant construction, plant retirement, and updated emissions rates and marginal generation costs.
5. High Wind Future: In this scenario, we modify the future case to add wind plants sufficient to produce 20% of generation.

Finally, for each scenario, we evaluate uncontrolled electric vehicle charging, in which drivers plug in their vehicles immediately after the last trip of the day, and controlled charging, in which we optimize the vehicle charging to minimize the cost of generating electricity. In the controlled charging scenario, vehicle charging can occur any time between the last trip of the day and the first trip of the following day, so long as the battery is fully charged for the next trip.

When choosing the scenarios to model, we consider the tradeoff between modeling a future year when electric vehicles are expected to make up a larger portion of the vehicle fleet vs years in the recent past for which we can more confidently model the power grid. We choose 2010 as the base case, as it is the latest year for which complete data on power plant costs, emission rates, and operation, wind generation, load, and transmission constraints are available. We choose 2018 for the future grid scenarios because of an available EPA dataset predicting the characteristics of the power plant fleet (including operating costs) for that year. The three different battery sizes in the analysis span the range of sizes seen in popular, existing electric vehicles. We use the a Chevy Volt sized vehicle as the base case, as it is an intermediate range plug-in hybrid, midsized vehicle capable of driving the currently observed daily driving profiles without concerns about vehicle range.

Optimization of the Power System. To determine the effects of electric vehicles on the operations of the power system, we use the PJM Hourly Open-source Reduced-form Unit-commitment Model (PHORUM), an open-source unit commitment and economic dispatch model developed at Carnegie Mellon University.[11,12] This model uses mixed integer linear programming to minimize the costs of operating the power plants in the fleet while satisfying load, operating constraints of the power plants, and transmission and reserve constraints of the system. We modify PHORUM to incorporate plug-in electric vehicle charging, both controlled and uncontrolled, adding equations for battery constraints and charging requirements. The Supporting Information includes the complete set of equations in the model. The model optimizes each day using a 48 h window, and then steps forward 24 h, optimizes the following 48 h window, and repeats. The operating constraints of the power plants in the model include minimum generation levels, ramp rate constraints, and minimum on and off times. To account for outages, we derated the capacity of the power plants using the equivalent availability factor for each plant type and month of the year, as in ref 11. The model represents transmission constraints as hourly maximum power levels that can be transferred among five different transmission-constrained regions in PJM. The Supporting Information includes the description of the full model.

The model uses simplified reserve constraints. Most unit commitment models require that spinning reserves be within the ramping capability of active power plants but never call on those reserves. In PHORUM, instead of co-optimizing an energy and reserve market, as is actually done in PJM, the total load includes the reserve requirement, as though the system always uses the operating reserves. This simplification decreases the run time by an order of magnitude, allowing for the examination of a wide range of scenarios using data for the entire year. The additional generation due to reserves is constant between scenarios, because n-1 security for the power plants (where the system maintains sufficient reserves to meet load if the largest power plant in each region were to go offline) determines this amount for each transmission-constrained region. We expect the emissions from this extra generation to also be similar across scenarios and so would largely cancel out

DOI: 10.1021/es505822f
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in the comparison. Additionally, the potential error introduced is small: adding the reserves as load increases locational marginal prices (LMPs) by less than 5%, and the error compared to historical 2010 LMP's is lower than simply omitting the reserves.[11]

Data. *Power Plant Fleet.* The power system used in this study is based on PJM in 2010. PJM is an interesting power system to examine, as it is the largest independent system operator in the United States by population and has a large installed coal capacity. The data for the power plants comes largely from the NEEDS dataset (v.4.10)[13] but also includes data on power plant operating parameters from other sources like the Energy Information Administration (EIA) and PJM reports.[11] To include transmission constraints, we rely on PHORUM, which uses publically available PJM data. This model has been validated to simulate PJM prices reasonably well.[11] It divides the PJM system into five transmission-constrained regions connected by six transmission interfaces, as shown in Figure 1. Each transmission interface consists of several actual transmission lines PJM identified as causing about half of the congestion costs.[14] Transmission constraints can affect the value of controlled charging and the resulting emissions. For instance, reducing the vehicle charge rate in population centers on the East Coast may ease congestion at peak load times, allowing the use of cheaper power plants, with different emission profiles, for charging the vehicles.

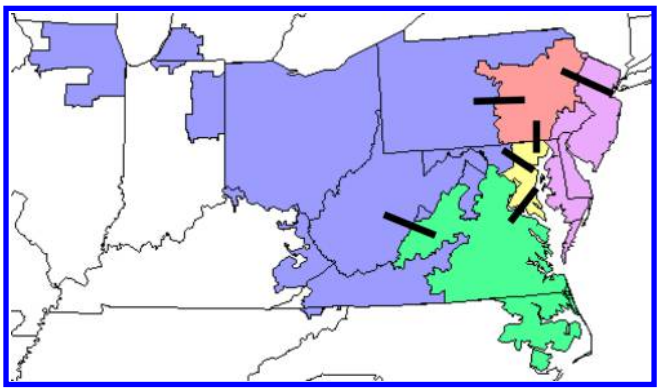

Figure 1. PJM power system divided into five transmission-constrained regions with simplified, power-limited transmission constraints between regions, represented by the black bars.

For scenarios 1−3, we use power plant emission rates from the 2010 eGRID dataset for CO_2, SO_X, and NO_2 emissions[15] and the 2005 NEI dataset for VOCs and PM 2.5 emissions[16] divided by the generation from eGRID 2005 (2005 is the most recent year for which both NEI and eGRID data could be matched, allowing for the calculation of an emission rate). For plants that were not present in the 2005 datasets, we assumed emissions rates were equal to the capacity-weighted average for each plant type. The majority of plants missing in the 2005 datasets were natural gas plants. For the future grid scenarios, we update the dataset with power plant additions, retirements, emission rates, and marginal costs from the EPA Parsed Results for 2018.[17] These results come from the EPA's Integrated Planning Model base case, which accounts for current regulatory constraints, including the Clean Air Interstate Rule (CAIR) and the Mercury Air Toxics Standards (MATS). We do not include any changes from the proposed existing source CO_2 rule, as it is still unclear what the final implementation will look like and what will be its exact effects. The future scenarios do not take into account any transmission expansion, but we do examine a sensitivity case with no transmission constraints.

To model wind power in PHORUM, we need hourly wind output data, which the EPA data do not include. In the future base case (scenario 4), we add wind generation using hourly wind profiles from NREL's Eastern Wind Integrations and Transmission Study (EWITS) dataset.[18] The EWITS data set contains 5 min modeled wind data for sites across the Eastern Interconnect that we aggregate to hourly data. We add sites in each PHORUM transmission region in order of capacity factor to produce the same aggregate annual amount of wind energy within that region that is forecasted in the EPA Parsed Results. In the high future wind scenario (scenario 5), we instead add sufficient wind sites to meet 20% of load, taking the EWITS sites from within the PJM boundaries with the highest capacity factors. The Supporting Information provides a summary of the relevant information obtained from each specific dataset.

Nonvehicle Load. To model the effect of vehicle load on the dispatch of power plants, we need to account for the baseline nonvehicle load. For the 2010 scenarios (scenarios 1, 2, and 3), we used hourly load data for PJM for 2010.[19] For the future grid scenarios (scenarios 4 and 5), we scaled the 2010 load data by a constant factor, which we calculate by dividing the forecasted total U.S. electricity load in 2018 by the total U.S. electricity load in 2010.[20] Using a simple scaling factor to calculate the future load assumes the use patterns and ratios of consumers for each use pattern remains constant as population increases. In practice, use patterns may differ in the future, but we lack hourly predictions of how load will evolve.

Plug-in Vehicle Fleet. Vehicle driving profiles are the basis for estimating the demand for electricity for vehicle charging. We model the driving profiles using data from the 2009 National Household Travel Survey.[21] This dataset contains all the trips traveled in 1 day for approximately 100 000 passenger cars across the United States, giving the start and finish time, location, and distance traveled for each trip. We assume that uncontrolled charging happens at home starting immediately after the last trip of the day and proceeds at the maximum charge rate. Controlled charging can happen any time between the last trip of the day and the first trip of the next day, but the battery must be fully charged in that time period. Because of the binary variables needed to represent each driving profile in the case of controlled charging, we select a subset of 20 vehicle profiles from the entire dataset for tractability. We selected and weighted these subset vehicle profiles to optimally represent the aggregated data set, following the method in Weis et al.[12] Further, for this analysis, we considered a 10% electric vehicle penetration of the passenger vehicle fleet (Weis et al.[12] suggest that generation cost implications are nearly linear with electric vehicle penetration in NYISO). We allocated electric vehicles to each transmission region proportional to population, so vehicles contribute most to load in the population centers on the east side of PJM and the Chicago area, and we examine alternative adoption patterns in sensitivity analysis.

Valuation of Health and Environmental Damages. The output of PHORUM includes hourly generation from all power plants in the PJM system. Using the emissions factors previously described, we then estimate total emissions for each power plant, and we estimate damages from these emissions using the AP2 model, the newest version of the Air Pollution Emission Experiments and Policy analysis (APEEP) model.[22] This model estimates monetized marginal damages that result from the emissions of five air pollutants (SO_2, NO_X,

DOI: 10.1021/es505822f
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NH_3, $PM_{2.5}$, and VOCs) in each county in the U.S., given baseline U.S. emissions from the National Emissions Inventory for the year being modeled. Using an air quality and transport model, the AP2 model first quantifies the change in pollutant concentrations that result from an additional ton of each pollutant emitted in each county using an air quality and transport model. The model then calculates human exposure to the increased concentrations based on the populations of the affected areas and estimates the change in morbidity and mortality associated with such exposure based on epidemiological dose−response models for each pollutant. The model also includes reductions in recreational use, agricultural yields, visibility, and other effects based on the increased concentrations. However, health impacts, monetized using a $6 million value of statistical life, make up the majority of damages. These damage estimates are available for each pollutant for emissions at ground level vs at stack height. We use the stack height damages in this study, as all emissions come from power plants. AP2 damage values are available for 2002, 2005, 2008, and 2011. However, only the 2005 AP2 model explicitly incorporates uncertainty as a distribution of potential outcomes, so we use the 2005 damage values as our base case and show robustness of our findings for other years in the Supporting Information. This uncertainty includes a range of values for the value of a statistical life and other key input parameters but not a measure of error in the simplified air quality model or in the epidemiological studies. We also compare our results in a sensitivity case to damages calculated using a different model of marginal damages, EASIUR. This model was developed using regressions on data from a state-of-the-science air transport model and only includes human health effects. The Supporting Information provides more details about the EASIUR model.

3. RESULTS AND DISCUSSION

Results. We find that controlling the charging of plug-in electric vehicles can significantly reduce the cost of generating electricity for vehicle charging, but with the tradeoff of increasing coal generation and therefore increasing emissions and health and environmental damages in many cases. The reductions in generation cost range from 23% to 34% depending on the scenario, as shown in Table 2. The cost reductions come from lowering fuel, operating, maintenance, and start-up costs through changes in plant dispatch.

Table 2. Reduction in Annual Generation Costs via Controlled Charging vs Uncontrolled Charging for the 10% Electric Vehicle Fleet

scenario	reduction in annual generation costs with controlled charging		
	total reduction	per vehicle reduction	% of total charging generation costs
Base Case (Volt)	$130 million	$54	32%
Smaller Battery (Plug-in Prius)	$54 million	$22	30%
Larger Battery (Tesla)	$137 million	$58	24%
Future (2018 Grid)	$87 million	$37	23%
High Wind Future	$115 million	$49	34%

Figure 2 shows the power generation attributable to vehicle charging with controlled and uncontrolled charging, given a 10% electric vehicle penetration. The reductions in generation costs associated with controlled charging for scenarios 1−4 stem primarily from shifting generation away from higher-marginal-cost natural gas plants to lower-marginal-cost coal plants. Controlled charging allows for this shift in generation by delaying charging from peak demand hours, when drivers arrive home, to later at night, when the cheaper coal power plants are available. In the high wind case, controlled charging also allows for the system to use approximately 1 TWh of wind energy that would have otherwise been lost through curtailment. The pumped hydro storage systems in PJM provide flexibility in the uncontrolled charging scenarios, which causes the slightly higher generation observed in each uncontrolled charging case due to efficiency losses from storing and retrieving energy.

Figure 3 summarizes the resulting changes in emissions under controlled charging. The shift toward more coal generation causes an increase in emissions of CO_2, SO_2, NO_X, and $PM_{2.5}$ in scenarios 1−4, compared to uncontrolled charging in each scenario. In these scenarios, VOC and NH_3 emissions decrease with controlled charging. Natural gas power plants are a larger source of these emissions than coal plants, so this reduction is not surprising given the shift toward coal generation associated with controlled charging in these scenarios. In scenario 5, CO_2, $PM_{2.5}$, VOC, and NH_3 emissions decrease with controlled charging as a result of decreases in total fossil fuel use that take place because the system is able to integrate more wind compared to the uncontrolled charging scenario. However, controlled charging in this high wind scenario continues to drive an increase in SO_2 and NO_X emissions compared to uncontrolled charging. In this scenario, emissions for all pollutants from natural gas plants decrease, but the increase in emissions of SO_2 and NO_X from coal plants is larger than the reduction in emissions of these pollutants from the natural gas plants. The Supporting Information provides a detailed breakdown of the total emissions by fuel type for the high wind scenario.

Figure 4 summarizes total social benefits (reductions in operation costs plus reductions in externality costs) due to controlled charging. Error bars display a 95% confidence interval for net benefits from the quantified uncertainty in the AP2 model (we explore other sources of uncertainty in our model via sensitivity analysis). We find that in the recent grid (scenarios 1−3), increased social costs from controlled charging emissions outweigh reductions in generation cost. These emissions costs stem largely from increased morbidity from SO_2 emissions, primarily due to secondary particulate matter formed in the atmosphere. In scenario 4, controlled charging leads to an increase in damages roughly equivalent to the reductions in generation costs, resulting in near-zero net benefits. In scenario 5, with high wind penetration, reductions in generation cost are larger than the increase in emissions externality costs.

Because our model cannot directly account for many sources of uncertainty, we test the robustness of these results using a number of sensitivity cases. We run cases with electric vehicles concentrated in urban areas, no transmission constraints in the future grid, additional reserves for wind generation, and two additional fuel price scenarios in the future grid. We also evaluate the changes in emission damages using AP2 point estimate values from 2002, 2008, and 2011 as well as with an alternative model of marginal emission damages, EASIUR. The

DOI: 10.1021/es505822f
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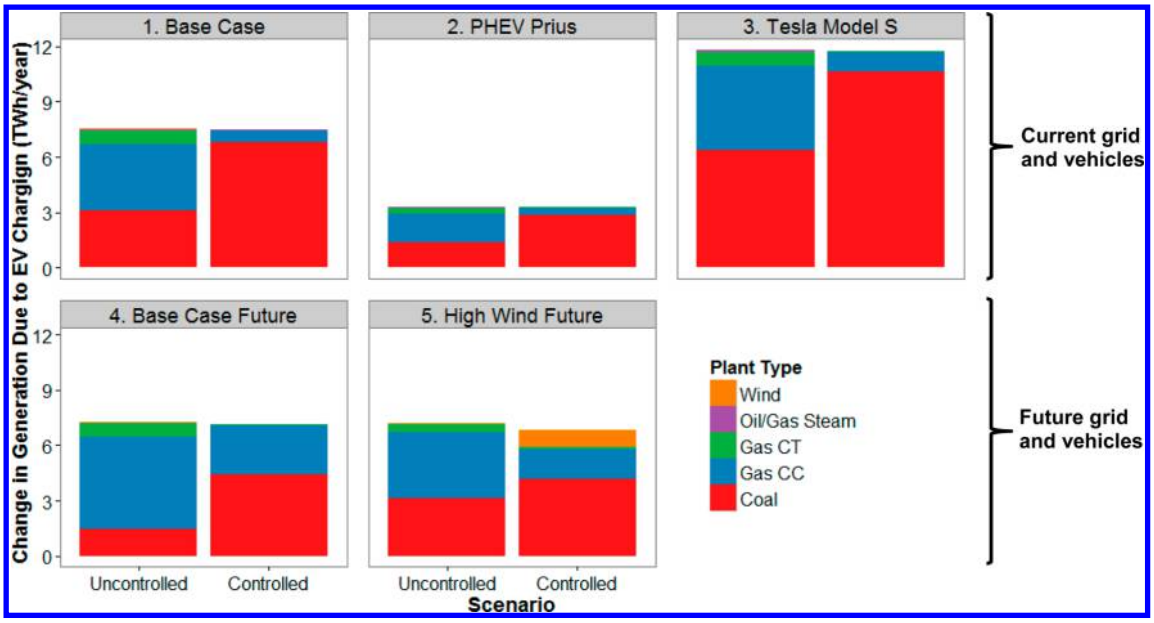

Figure 2. Change in system generation due to electric vehicle charging for controlled and uncontrolled charging for a 10% electric vehicle penetration. The recent grid scenarios are based on the 2010 PJM power system with the 2010 GREET $PHEV_{35}$ as the base case vehicle. The future grid scenarios are based EPA's projections for the 2018 PJM grid with the 2015 GREET $PHEV_{35}$ as the vehicle. CC = combined cycle, CT = combustion turbine.

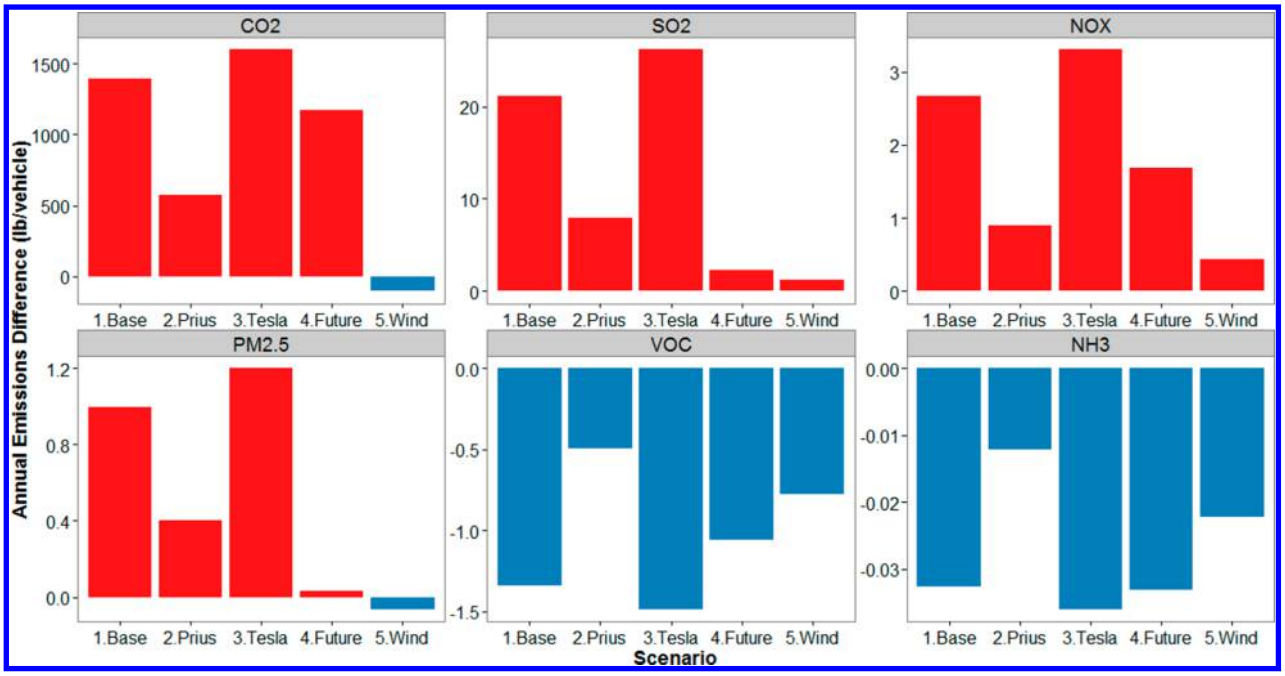

Figure 3. Average change in emissions due to controlled vs uncontrolled charging in PJM per vehicle per year. Red columns depict increases in emissions due to controlled charging; blue columns show decreases in emissions due to controlled charging.

Supporting Information includes detailed results for these cases. Our key finding, that controlled charging of electric vehicles produces negative net social benefits in the recent grid but could produce net positive social benefits in a future grid with sufficient coal retirement and wind penetration, is robust across all scenarios.

We do not intend for our representation of the future PJM grid to be a perfect prediction of the grid in 2018. It is difficult to know exactly which plants will choose to upgrade their emission control technology or retire, and the predictions for 2018 do not include the effect of the proposed carbon policy for existing sources, since its exact effects are difficult to predict. Instead, the future grid scenarios provide a plausible grid with a lower emissions footprint. We see that even with substantially more wind power than is predicted by 2018, along with plausible improved emissions rates and coal retirements, the net benefits from controlling the charge rate of electric vehicles may be small, and we cannot be certain they will be positive, as the marginal damages from emissions change over time.

There are limitations to the model outside of the scope of sensitivity cases we examined. A detailed discussion of this study's limitations is provided in the Supporting Information.

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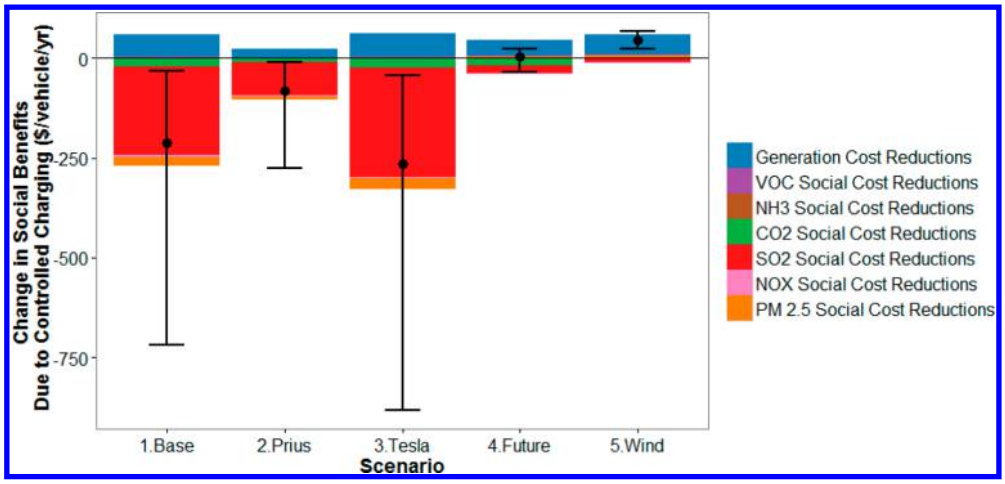

Figure 4. Reduction in annual generation cost and external emissions costs due to controlled charging compared to uncontrolled charging ($\$_{2010}$). Stacked bars show the change in generation cost combined with the median damages by pollutant assuming the 2010 social cost of carbon given by the Office of Management and Budget ($31 in $\$_{2010}$).[23] Black dots show the change in net social benefit due to controlled charging with error bars representing a 95% confidence interval, reflecting uncertainty in emissions damages quantified in the AP2 model. We examined other sources of uncertainty in sensitivity analysis (see the Supporting Information).

Although some of these limitations are difficult to quantify in the current modeling framework, we do know that the 2010 PHORUM model is fairly representative of reality despite the limitations. Lueken and Apt analyzed the capacity factor of plants dispatched by PHORUM and compared them to actual capacity factors from 2010. They found that the mean error in capacity factor was 3.6%.[11] Additionally, although the model cannot capture all factors that affect grid operations and we do not claim to perfectly predict operations in either time period, it is nevertheless useful to know how an idealized grid with realistic constraints would respond to EV load with different charging patterns to provide insights about real-world systems.

We find that although controlled electric vehicle charging may significantly reduce the generation cost of electric vehicle charging in PJM, it may also create increases in emissions externality costs due primarily to increased use of coal-fired power plants. The net implication is that controlled electric vehicle charging creates negative net social benefits in the recent grid scenarios but might produce positive net social benefits in a future grid with sufficient coal retirement and wind penetration. This finding is robust to uncertainty in vehicle adoption patterns, transmission constraints, reserve requirements, fuel prices, and air emissions implications.

In general, controlled charging has potential for reducing generation costs, but its net implications depend on the characteristics of the power plant fleet. In other regions with tighter environmental regulations, more renewable generation, less coal power, and/or inexpensive natural gas plants, controlled charging could lead to lower environmental and health damages. Our results also suggest that the externality costs missing from the current power system operations based on generation cost minimization are substantial and should be considered when making policy decisions to avoid large increases in human health and environmental costs.

■ ASSOCIATED CONTENT

Ⓢ Supporting Information

Formulation of the unit commitment problem in PHORUM, summary of information obtained from each dataset, emissions by plant type for the high wind scenario, per vehicle emissions and damages, additional sensitivity cases, and limitations. This material is available free of charge via the Internet at http://pubs.acs.org.

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Notes

The authors declare no competing financial interest.

■ ACKNOWLEDGMENTS

Special thanks to Nick Muller for his support with the APEEP and AP2 models and to Peter Adams and Jinhyok Heo for their help with the EASIUR model. The Doris Duke Charitable Foundation, the Richard King Mellon Foundation, the Electric Power Research Institute, and the Heinz Endowment provided support for this research through the RenewElec project (www.renewelec.org). The National Science Foundation also provided financial support through a Graduate Research Fellowship. Findings and conclusions are the sole responsibility of the authors and may not represent the views of the funding entities.

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